ECONOMIC ANALYSES OF AGRICULTURAL LAND-USE CHANGE AND AGRO-ECOSYSTEM SERVICES FOR WATERFOWL IN NORTH DAKOTA

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MASTER OF SCIENCE

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ABSTRACT

Understanding the relationship between crop production and wildlife habitat in North Dakota – which contains a large portion of the Prairie Pothole Region – will be essential to the continuation of both in a region facing increasing pressure on its natural resources. This research aims to better understand the relationship through economic analysis of land-use change within the region. Utilizing yield, price and budget data for crops in North Dakota, cumulative distribution functions were constructed to compare crops between nine regions within North Dakota. This research will then be able to suggest regions where crops beneficial to wildlife habitat as well as to the producer – notably winter wheat – could be pursued.

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DEDICATION

This thesis is entirely owed to my wonderful family. Without my supportive and caring wife, I would not have been able to embark on such a valuable education and experience. To my daughter, Wren, you bring joy to my life in so many ways, thanks for keeping me on my toes.

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CHAPTER 1: POTENTIAL BENEFITS OF HARD RED WINTER WHEAT CROPPING SYSTEMS FOR FARMERS AND WILDLIFE

Abstract

The decline in Conservation Reserve Program (CRP) enrollment has raised concern for numerous environmental issues. Among these concerns are soil erosion, water quality, and wildlife habitat. While research has estimated nest success rates for CRP land, natural habitat, and crop land in the Prairie Pothole Region, finding a substitute for the loss of duck nesting habitat is in the early stages. Preserving the duck population is not only important to Ducks Unlimited and the Audubon Society; it is also the keystone to the industry providing goods and services to migratory waterfowl hunters valued at over one billion dollars in the United States (US Department of the Interior 2006). Converting cropland acres to winter wheat is one way to provide nesting habitat while allowing farmers to continue crop production. By including one year of winter wheat in a four crop rotation, the duck population could be increased by 0.08 ducks/ac/yr. Using yield data from NDSU Extension Service and price and insurance data from NASS, this study creates cumulative distribution functions of expected revenue for dominant crops in North Dakota to compare crop profitability. This research shows that winter wheat is currently competitive in two North Dakota regions with the potential for breeding programs or policies to increase this to four regions.

Introduction

Not only does winter wheat improvement have the potential to enhance producer profitability but also the potential to increase crop diversity in the Northern Great Plains (NGP) while also providing better nesting habitat for ducks. The relatively undeveloped genetic potential of winter wheat lines for the NGP suggests that perhaps the marginal cost of developing new, substantially more profitable lines for North Dakota might be low compared with further development of other crops. This makes winter wheat a prime candidate for public and private investment in crop improvement programs. In North Dakota, hard red winter wheat has mostly been a cropping afterthought for several decades, comprising between 0.2% and 3.3% (USDA NASS 2013) of total field crop area in the state from 1993 to 2012. But recent years have seen increasing research into the crop in the form of Ducks Unlimited research, the formation of the Winter Cereals: Sustainability In Action (WCSIA) partnership and North Dakota State University (NDSU) restarting its breeding program in 2010 – joining South Dakota State University, Colorado State University, and Washington State University winter wheat breeding programs, among others. WCSIA is a joint research and education initiative from Ducks Unlimited and Bayer CropScience, as well as several colleges and universities, and is already achieving success in both winter wheat development and adoption. However, farmers are unlikely to substantially increase winter wheat plantings without strong evidence that including or increasing winter wheat in their crop rotations can improve profits while maintaining or lowering their level of risk when compared to their current planting portfolio.

Several studies of winter wheat genetics have indicated that it has great potential for improved productivity. Amongst these studies, Zhang et al. (2010) show that winter wheat has high genetic diversity, indicating strong potential to increase productivity and profitability of the crop. This potential for development encourages research, both now and in the future, that could lead to further improvements in winter wheat yields, disease resistance, milling qualities, and winter hardiness, as well as allowing for later planting dates. Past winter wheat breeding has already led to more winter hardy varieties (e.g. Roughrider, Norstar, and Agassiz), improved resistance to some common diseases, and improved yields (Zhang et al. 2010; Cox 2010; Ransom and McMullen 2008). The continuation of current breeding programs can help expand the use of this genetic potential. The rekindling of the winter wheat breeding program at NDSU in 2010 will showcase this potential within a few years.

Other studies have noted winter wheat's potential for future gains in yield performance and improved quality through increased or improved breeding efforts (Reynolds et al. 2009, Zhang et al. 2010, Graybosch & Peterson 2010). One specific opportunity is the potential baseline yield increase of 50% or more by improving winter wheat photosynthesis through natural variation in Rubisco's catalytic rate or adopting C_4 metabolism (Reynolds et al. 2009). The potential to improve winter wheat yields could encourage increased acreage in the future, a boon for duck nesting habitat in the NGP.

While the current corn/soy dominated cropping system allows for greater specialization in machinery for harvesting, storage, et cetera, there are some potential problems with this plan in the long run. Specifically, some evidence indicates monocultures and systems with low crop diversity experience lower yields, larger disease losses, and higher soil erosion rates than more diverse crop rotations (Berzsenyi et al. 2000; Tilman et al. 2001; Beck 1998). Low diversity cropping systems are more likely to be devastated by disease, are less capable of mitigating climate change losses, and do not support as much animal diversity as a polyculture system can (Chateil et al. 2009). Adding winter wheat to a corn/soy or spring wheat/soy rotation could help mitigate these risks.

It is also important to note that agricultural practices influence wildlife populations and the resiliency of natural ecosystems. For example, winter wheat provides better duck nesting habitat and improves nest success rates relative to corn and other spring-seeded crops (Duebbert and Kantrud 1987) (Devries et al 2008). High quality duck nesting habitat in the Prairie Pothole Region (PPR, see Figure 1) of the NGP is critical to maintaining duck populations, as the region is a key duck breeding ground (Klett et al. 1988) (Reynolds et al. 2006) (WHMI 1999); providing up to 75% of the nation's ducks during wet years (WHMI 1999). Developing the genetic and economic potential of winter wheat can allow this duck-friendly crop to be competitive with crops in current rotations in the NGP and PPR.

Quantifying the advantage presented by winter wheat over spring-seeded crops in terms of nesting habitat is an essential component in this research. Over the past few decades there have been a number of studies focused on determining just what type of land provides the best duck nesting habitat in terms of nesting frequency and success rates. Monitoring cropland for waterfowl nesting faces concerns for potential crop damage in the search process and, as such, previous nest searches were typically limited in frequency or timing (Klett et al. 1988) (Higgins 1977) (Greenwood et al. 1995). Devries et al. (2008) were able to complete 3 to 4 nest searches on 4,274 ha of cropland, including spring-seeded and fall-seeded crops, determining nesting frequency as well as nest success rates.

The Conservation Reserve Program (CRP) was established in 1985 to mitigate environmental quality degradation by removing environmentally sensitive land from production (Allen & Vanderever 2003). Currently and historically, CRP land has provided significant duck nesting in the PPR (Reynolds et al. 2006). However, CRP enrollment in North Dakota has decreased by an average of 81,000 ha yr^{-1} from 2008 to 2012 (USDA NASS 2013a). If CRP enrollment continues to decline, maintaining duck nesting habitat quality and quantity will depend increasingly on the compatibility of agricultural practices and duck nesting. Increased winter wheat adoption has the potential to mitigate some of the anticipated adverse effects of reduced CRP enrollment in the PPR.

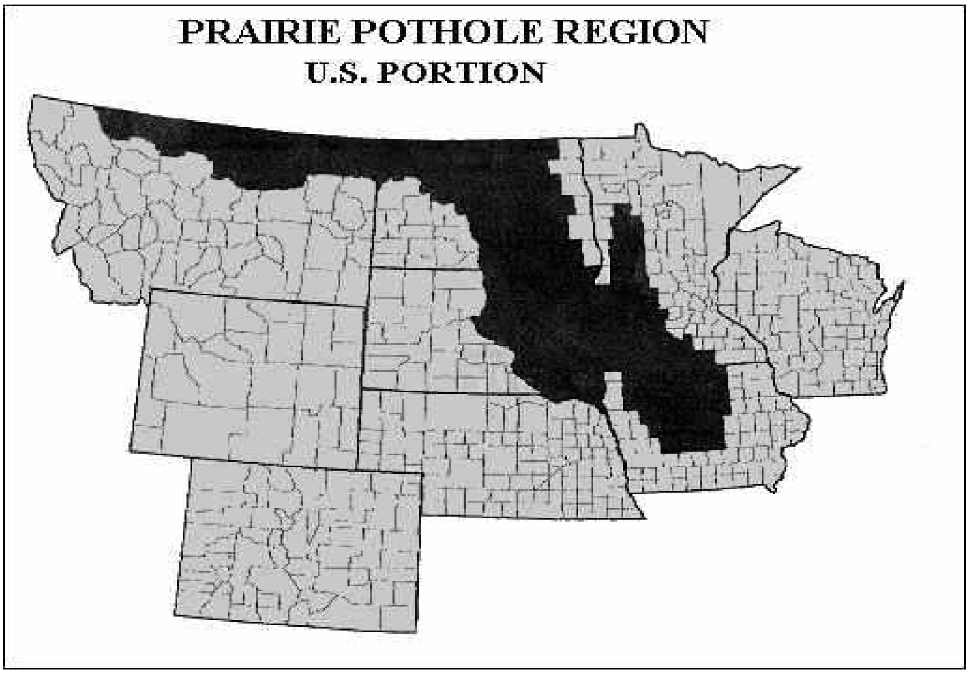

Figure 1: PPR map from Kraus 1997.

The USGS survey on CRP land (Allen & Vanderever 2003) showed that program participants noticed many non-financial benefits from enrolling. These benefits ranged from reduction of soil erosion to positive changes in wildlife populations. While this survey is nine years old, it is important to note that 49% of respondents desired the CRP to continue without significant change and an additional 32% desired an increase in management with an increase in funding (Allen & Vanderever 2003). The USGS survey also found there was an overwhelming majority of respondents that believe wildlife habitat is a priority (> 90% nationally). It is important to know that wildlife habitat is a large national concern since large amounts of CRP acres may expire without renewal over the next few years. This loss of habitat can be mitigated with the conversion of planted acres to fall-seeded crops such as winter wheat, providing suitable habitat for spring nesting waterfowl and other wildlife.

Farmers will only plant more winter wheat if the crop can increase the profitability of their operations. While the WCSIA initiative has already successfully convinced some farmers to adopt winter wheat, finding a crop rotation that can further improve yields and profits is essential to compete economically with current regionally predominant rotations. Without a rotation demonstrated to produce similar revenues to current rotations, increased winter wheat adoption is likely to be minimal. The objective of this research is to identify the most economically beneficial winter wheat rotation with the least risk, using currently available commercial lines of winter wheat. Finding an optimal winter wheat rotation will not only provide a working example for farmers to implement in the near-term but also provide a current economic benchmark for winter wheat in North Dakota growing conditions, against which progress in winter wheat improvement can be measured.

The study by Devries et al. (2008) was instrumental in comparing the benefit provided by winter wheat over spring-seeded crops by providing estimates for duck nesting frequency as well as nest success rates for several crops. To determine the effects a rotation would have upon duck population numbers, these numbers were adjusted to an annual average benefit to duck population per acre. Combining the financial results with the duck population effects allowed for determining a region best suited to provide benefits for both the producer as well as for duck nesting habitat. While studies have also been done studying nest success rates in Grassland/CRP (Klett et al. 1988), the difficulty arises in establishing a relationship between the numbers of the studies. In Devries et al. (2008), no-till winter wheat had a 38% nest success rate but Klett et al. (1988) listed idle grassland having only a 21% nest success rate.

While the focus of this research has been on benefits to waterfowl nesting habitat, there are other species that will benefit from the improved habitat brought by increased winter wheat acreage. A section of the PPR in North Dakota (Figure 1) overlaps a stretch of the breeding range for ring-necked pheasants (Figure 3, below). As mentioned in Duebbert and Kantrud (1987) and Snyder (1984), pheasants will also benefit from improved nesting habitat with increased winter wheat planting. The increase in land with vegetative growth in spring due to winter-seeded crops improves nesting habitat for a large number of species in the Northern Great Plains. Even though this is cropped land, there is also far less machinery used in the spring to disturb breeding wildlife. The potential to improve habitat for more than waterfowl should not be overlooked and could be included in further analyses.

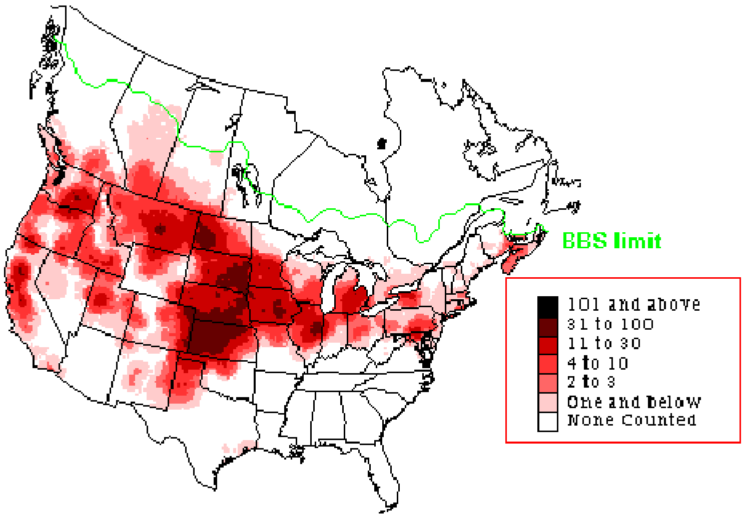

Figure 2: Pheasant breeding range (WHMI 1999).

While much has been researched with regard to winter wheat and duck nesting habitat (), there is a gap in the literature for identifying the path to achieve continued acreage suitable for duck nesting. This research will [1] compare producer profits in North Dakota budgeting regions across crops, [2] evaluate the potential gain to duck population numbers by including winter wheat in a crop rotation, and [3] determine the North Dakota region with the greatest potential for winter wheat adoption.

Methodology

Conceptual Framework

Conceptually, selection of a crop rotation is a business decision. Risk-neutral producers choose the rotation expected to be most profitable from among a set of feasible rotations. Thus, the farmer's decision framework can be modeled as follows:

$$\max_{j\in\{1,2,\cdots J\}} E(\pi) = \sum_{j=1}^{J}\sum_{i=1}^{N} w_{ij}[E(p_i)E(y_{ij}) - c_i] \tag{1}$$

where π is profit, w_{ij} is the frequency of crop *i* in rotation *j*, p_i is the price of crop *i*, y_{ij} is the yield of crop *i* in rotation *j*, c_i is the explicit (or cash) cost of producing crop *i*, $E(\cdot)$ indicates the variable in brackets is evaluated at its statistical mean, *J* is the number of feasible rotations, and *N* is the number of crops involved. Note that the model allows for rotational effects on each crop's mean yield. Necessary data includes crop yield, price histories, and budgeting costs.

Data

Several datasets were utilized for hypothesis testing and simulation purposes. Crop yield data are from two sources: 1) The Conservation Cropping Systems Project (CCSP) from 2002-2011 (CCSP 2011), and 2) NDSU Agricultural Experiment Station Variety Trial Results (VTR) from 2001-2012. Price history data came from NASS Quick Stats and budgeting costs were retrieved from NDSU Extension Service. Adjustments for inflation to price history data would be completed using consumer price index (CPI) values from Bureau of Labor Statistics (BLS).

The CCSP—a demonstration farm located near Forman, ND operated through the Wild Rice Soil Conservation District—provided our initial crop yield data set (CCSP 2011). The farm is sponsored by a large number of private corporations, public service organizations, and individuals. CCSP demonstrates 13 distinct crop rotations combined with various types of conservation tillage. Each of the 13 crop rotations is replicated three times, wherein, each crop is replicated three times annually within each rotation (CCSP 2013). Thus, for a three-crop rotation, nine plots are planted each year—three plots for each crop in the rotation. Table 1.1 provides the specifics for each crop rotation under study. The spatial extent of the data is limited to this single location, and the data span a period of nine years. As each experimental plot had completed at least one full cycle of its crop rotation, the effect of temporal limitations was assumed to be small.

Table 1.1: CCSP crop rotations (CCSP 2013)

Identifier	**Crops in Rotation**
A	spring wheat/winter wheat/corn/soybeans
B	spring wheat/winter wheat-st/corn/soybeans
C	spring wheat/winter wheat-biost/corn/soybeans
D	spring wheat-st/corn/soybeans
E	spring wheat-cc/soybeans
F	corn/soybeans-st
G	spring wheat-cc-st/corn/soybeans/corn/soybeans
H	HRSW - HRWW - Corn - Soybean - Corn – Soybean
I	spring wheat/winter wheat/flax-st/corn-st/corn/soybeans
J	winter wheat/soybeans/corn-st/corn/flax
KH	winter wheat-bio-strip/corn/soybeans
N	spring wheat/winter wheat/alfalfa/alfalfa/corn/soybeans
Q	spring wheat/winter wheat/soy/corn/soy/corn/soy

Notes: st denotes strip till operation, cc - denotes cover crop
For 2012 added ww as cc to rotation G after spring wheat. Use strip till in spring

The VTR data come from North Dakota Agricultural Experiment Station locations throughout the state, including sites in 36 counties (NDSU REC 2013). The mean yield for each crop at each experimental location is provided, along with the coefficient of variation in yield. This information is used to simulate yields for the crops regularly grown in each of the NDSU

Extension Service’s delineated budgeting regions (NDSU Farm Management 2013). The geographic dispersion of these data mean results can vary across the state, and will be applicable outside the limited geographic scope of the CCSP. These data cover a much larger geographical area and a slightly longer time period than the CCSP data.

Crop Cover Data

Determining regional cropping patterns required the use of GIS data, specifically the USDA NASS Cropland Data Layer (CDL) (USDA NASS 2013b); the NASS CDL is a raster, geo-referenced, crop-specific land cover data layer. The CDLs for 1997 through 2005 have ground resolutions of 900 meters^2. These CDLs are produced using satellite imagery from the Landsat sensor collected during their respective growing seasons. The CDLs from 2006 to 2009 have ground resolutions of 56 meters. These CDLs are produced using satellite imagery from the Landsat 5 TM sensor, Landsat 7 ETM+ sensor, and the Indian Remote Sensing RESOURCESAT-1 (IRS-P6) Advanced Wide Field Sensor (AWiFS) collected during their respective growing seasons. The CDLs after 2009 have ground resolutions of 900 meters^2. These CDLs are produced using satellite imagery from the Landsat 5 TM sensor, Landsat 7 ETM+ sensor, and the Indian Remote Sensing RESOURCESAT-1 (IRS-P6) AWiFS collected during their respective growing season. The CDLs were overlaid to identify crop rotations within fields. For each region, 10 fields were selected to determine crop rotation representation and find prevalent crops. These crop rotations were used as a basis for comparing our crop rotation budgets as we expect them to be among the most financially beneficial in their respective regions.

Historical crop price data from 1997 through 2012 for North Dakota were obtained from the NASS Quick Stats database (USDA NASS 2013a) and adjusted for inflation using annual

CPI ratios from the BLS (BLS 2013). NDSU Extension budgets for 2012 (NDSU Farm Management 2013) were used to account for cropping costs, included in which are insurance premiums, seed, labor, machinery, and other costs associated with planting and harvesting crops.

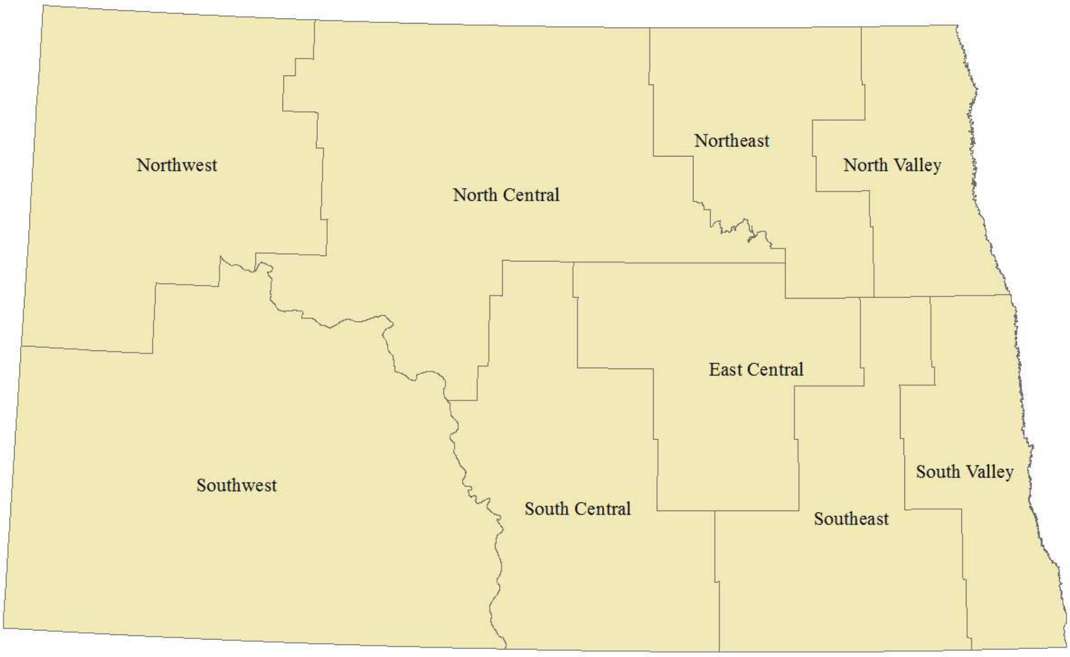

Figure 3: Crop budgeting regions for NDSU Extension Service.

NDSU Extension Service budgets (NDSU Farm Management 2013) were used to determine costs to calculate net profit per acre. These budgets assume crops are insured to 70% of average production history (APH). Crop budgeting would be incomplete without including crop insurance and loan deficiency payments (LDPs). Data for insured prices of crops were taken from the USDA's Risk Management Agency (RMA) (USDA RMA 2013); these values are listed in Table 1.2. Annual insured price observations cover the range from 1997 to 2012. Crop loan rates for 2012 were averaged over North Dakota using county values from USDA FSA. Only sugar beets and dry edible beans were already in regionally averaged values. Dry edible beans were averaged over North Dakota and the value used for sugar beets was an average for Eastern North Dakota – the region with the most prevalent sugar beet acreage – and Minnesota. In the special case of dry edible beans, where loan rates are divided into bean types, determining the loan rate to use required additional information on bean plantings in North Dakota. As navy and pinto beans dominate the commercial cropping acreage in North Dakota dry edible bean planting, an average of their insurance price histories was used (North Dakota Pesticide Impact Assessment Program 2000).

Modeling & Simulation

One important question that must be answered prior to further modeling or simulation is whether the yield of a given crop is significantly affected by the crop rotation in which it is included. A regression was conducted for each crop using data from the CCSP demonstration farm to test for such yield differences amongst rotations. The models were estimated as follows:

$$y_{jkt} = \alpha + \sum_{j=1}^{J-1} \eta_j D_j + \omega_t + \varepsilon_{jkt} \tag{2}$$

where y_{jkt} is the reported yield of the crop in rotation *j* for the k^{th} observation in year *t*, α is the yield intercept, J is the number of rotations in which the crop is grown, η_j is a deviation from the intercept yield—a fixed-effect—attributable to rotation *j*, D_j is an indicator variable equal to one for rotation *j* and zero otherwise, ω_t is a deviation from the intercept yield—a random effect—attributable to year *t*, ε_{jkt} is a stochastic error term, and ω_t and ε_{jkt} are uncorrelated and normally distributed with means zero and respective variances of σ_ω^2 and σ_ε^2. For each crop, a likelihood ratio test with $J-1$ degrees of freedom is used to determine whether the rotational effects on crop yield are jointly significant. If it is determined that the coefficients η_j are jointly insignificant, then $E(y_{ij})$ from equation (1) becomes $E(y_i)$. This modeling process is used to identify the parameters (mean and standard deviation) of the yield distribution for each crop.

Prices and costs were adjusted to 2012 US dollar values using the data described in the previous section for crop prices, input costs, and CPI values using equation (3). From each crop's set of adjusted annual prices, means and standard deviations were derived. For equation (3), *p* represents the CPI adjusted price, *q* represents the value before CPI adjustment, subscript *t* references the year, and *CPI* is the value of CPI corresponding to the subscript.

Table 1.2: Insured prices (adjusted for CPI)

Year	Corn ($/bu)	Soybeans ($/bu)	Barley ($/bu)	Sunflower confection ($/cwt)	Sunflower oil ($/cwt)	Canola ($/cwt)	Wheat ($/bu)
2011	6.13	13.77	6.05	36.22	31.12	26.84	10.09
2010	4.11	9.63	3.16	22.63	17.37	15.97	5.16
2009	4.28	10.59	3.96	24.98	21.77	21.25	7.17
2008	5.06	12.26	4.80	30.49	27.83	25.83	9.86
2007	3.87	7.75	3.10	20.70	15.72	14.72	4.93
2006	2.28	5.86	2.11	17.08	13.38	10.99	3.59
2005	2.59	5.88	2.76	16.34	12.52	12.58	4.11
2004	2.98	6.80	2.25	18.04	15.31	11.30	4.07
2003	2.74	6.61	2.56	18.21	14.16	11.84	3.93
2002	2.55	6.38	2.49	17.35	12.25	11.87	4.02
2001	2.59	6.95	0.21	16.46	12.05	12.05	3.63
2000	2.53	6.88	2.13	12.53	12.40	12.40	4.20
1999	2.89	7.23	2.48	17.91	13.78	17.50	4.55
1998	3.66	8.45	3.10	16.90	12.67	-	5.14
1997	3.50	8.80	3.29	18.59	15.73	-	5.51

Courtesy: Dr. Frayne Olson and USDA RMA (2013)

$$p_t = q_t \cdot \frac{CPI_{2012}}{CPI_t} \tag{3}$$

However, the rotation factors from CCSP data did not have statistically significant contributions to the yield data as determined by a mixed-effects model. This result may have been due to weather or other influences on the yields. For example: yields for the entire farm were drastically reduced in 2003 due to severe hail storms and this type of factor has an effect that greatly outweighs the influences we were attempting to observe. The attempt to include weather factors such as temperature, solar irradiance, and precipitation from the nearest weather station did not increase the influence of rotational effects to significant levels. A few of the sites listed previous planted crop but this information was not carried forward into our analysis since this was no longer a feasible consideration for this study with the change in dataset, as well as no longer considered necessary due to no statistically significant influence from rotations using CCSP data.

Analysis from this point on switched to utilizing NDSU Research Extension Centers' (NDSU REC) VTR data (NDSU REC 2013). The means and CVs of yields for each crop from each site for each year were used to generate 1,000 iterations for each observation as described in equation (4a) (1 iteration = 1 harvest cycle). Using the adjusted crop price received values from equation (3), equation (4b) was then used to simulate price distributions for each crops' iteration.

$$y_{ist} = \mu_{is} + z_t \cdot \delta_{is} \tag{4a}$$

$$p_{it} = \upsilon_i + z_t \cdot \delta_i \tag{4b}$$

Where y or p represents the yield or price, respectively, μ or υ represents the respective mean, z is a random number generated from a normal distribution, δ represents the corresponding standard deviation, i refers to the crop type, subscript s specifies the research site and subscript t

again references the iteration. As noted earlier, crops received payments for iterations with yields under 70% of APH for crop insurance (in North Dakota, spring, durum, and winter wheat have a shared average production history) and saw loan deficiency payments when the iteration of price was below the loan rate. Insurance premiums were given in NDSU Extension Service budgets (NDSU Farm Management 2013) and insured prices were found from the USDA RMA's website (USDA RMA 2013) with the assistance of Dr. Frayne Olson, NDSU Extension Crop Marketing Professor. These payments were calculated by identifying which iterations had yields below 70% APH (using the mean of the generated distribution as APH) and multiplying the shortage in yield by the insurance price. Allowing for insurance to be included in our iterations, yield protection or multi-peril crop insurance prices were regressed onto their respect crop's price received value for 2000 to 2011 (some crops had data back to 1997 and a couple through 2012). The regression was performed using the OpenOffice® function *linest* (OpenOffice 2013). The fits were then used to determine insured prices for each of the prices in the generated price distributions. Since all of our prices and costs were converted into 2012 dollars, crop loan rates for 2012 were used, except for sugar beets. As sugar beets saw a large price jump in 2011 (the last year we have price data for), the historic average was well below the loan rate, causing an overestimate of sugar beet revenue. To adjust for this, the loan rate from 2011 was taken to be a flat percentage of the marketing year crop price. This percent was then used to generate expected loan rates for the previous years through 1998 and the average of these values was used as the sugar beet loan rate. The loan rate for sugar beets is also given by pound of raw sugar where the marketing year price and insured price are given in per ton of sugar beet. The percentage of sugar refined from the beets, from NASS Quick Stats values (USDA NASS 2013a), was averaged to convert the prices to one set of units allowing for the derivation of a loan rate for sugar beets by the ton. The crop loan rates were then set as the lower limit for price distributions.

Using the values generated from equations (4a) and (4b) with crop budgets including projected costs to plant, grow, and harvest each crop, we calculated net profit for each of the 1,000 iterations of each observation using equation (5). Profit, Π, for each crop in each region r is estimated using equation (5). The price received is given by p and c represents budgeting costs. These profit distributions were then compared across crops within regions and by specifying crops to compare across regions. These comparisons were displayed through cumulative distribution functions (CDFs). The CDFs were compared against one another to determine the region's/crop's relative profitability and risk profiles.

$$\Pi_{ir} = y_{ist} \cdot p_i - c_i \tag{5}$$

Some regions' budget reports did not offer data on all crops we had data for; in these cases an OLS regression was fit for the available crop budgets in the region with all other regions and the closest fit region was used to estimate the budget values for the missing crop. Specific crop budgets that were not created by the NDSU Extension Service but had observations in the performance variety trials include: soybeans in the Northwest and Southwest regions.

Results

Since the intent of this research was to identify the most economically advantageous rotation containing winter wheat, finding data to compare yields from different rotations was the starting point for our research. The CCSP dataset used had over a decade of rotation-based yield data. However, using a mixed-effects model showed that the rotations present in the study did not have significantly different influences on crop yield. Given that the rotations chosen were those already commonly planted, it would be quite natural for these rotations to show little advantage over one another. In the case of weaker rotations, they would quickly be forced out of planting by more efficient rotations. Due to the lack of significant differences between rotations in the CCSP data, NDSU Extension Services' variety trial data were used instead to compare winter wheat across regions and other crop choices.

Table 1.3: Random effects model fit from R

	Coefficients				
	Estimate	Std. Error	t-value	Pr (>|t|)	
(Intercept)	-5.768308	18.930861	-0.3047	0.7606392	
Rotation B	5.151486	11.887339	0.4334	0.6648241	
Rotation C	4.755927	11.887764	0.4001	0.6891697	
Rotation D	4.720987	12.440736	0.3795	0.7043933	
Rotation E	5.031555	14.838907	0.3391	0.734604	
Rotation F	5.374467	14.857615	0.3617	0.71761	
Rotation G	4.360663	11.439113	0.3812	0.7031109	
Rotation I	-14.469307	11.220933	-1.2895	0.1974507	
Rotation J	37.852036	11.87498	3.1875	0.0014682	**
Rotation L	4.974362	10.830455	0.4593	0.646098	
Rotation M	-2.764909	13.993094	-0.1976	0.8433952	
Rotation N	9.617295	11.945104	0.8051	0.4208915	
Corn	140.069769	17.647321	7.9372	4.36E-15	***
Corn on corn	120.986066	20.067119	6.0291	2.13E-09	***
Flaxseed	10.970645	22.649923	0.4844	0.6282122	
Soybean	37.262292	17.533028	2.1253	0.0337482	*
Spring Wheat	55.42364	17.679897	3.1348	0.001757	**
Winter Wheat	64.327647	17.834123	3.607	0.0003212	***
Alfalfa	-0.098559	24.196068	-0.0041	0.9967506	
Canola	916.117463	31.228451	29.336	< 2.2E-16	***

Significance codes: *'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1*

The comparisons were implemented to find if there was a region where winter wheat acreage could be increased to benefit duck nesting habitat while also potentially improving producer profits. Expanding winter wheat planting further through policies or price supports is also a possibility worth investigation. The data for this study was limited by the trials available from the NDSU variety trails. Specific deficiencies realized during our analysis were the minimal crop data for the Southwest region and for sugar beets. In the Southwest, the only crops with trial data were soybeans and winter wheat. For sugar beets, trials only existed for the East Central and Southeast regions. Therefore we were unable to compare rotations in the Southwest or include sugar beet data for the North Valley region, where sugar beets have been planted on 100,000 acres each year since 1990 (USDA NASS 2013a).

Comparing winter wheat net revenues across regions revealed the North Central region as the most financially advantageous region to grow winter wheat[a]. Average winter wheat annual revenue per acre by region was: $130.13 in North Central, $87.39 in Northeast, $75.56 in Northwest, $34.98 in Southwest, -$10.70 in East Central, -$40.25 in South Valley, -$41.07 in Southeast, and -$44.79 in South Central. However, the best region for winter wheat revenue, North Central, only finished third in the region trailing canola at $304.69/ac and dry edible beans at $145.64/ac. Winter wheat did rank first in the Northwest region at $75.56/ac, ahead of durum wheat and sunflower, at $70.63/ac and $67.41/ac respectively.

When comparing two and three crop rotations, winter wheat performed well in the Northwest region. In the Northwest region, the spring wheat – winter wheat rotation (See Appendix A for each region's rotation CDF graphs and Appendix B for projected crop rotation net revenue tables by region) outperformed all other simulated rotations, with average annual net revenue of $64.51/ac. The South Valley region had few crops represented in the VTR data causing limited rotation projections. With fewer rotations to compete with winter wheat, with an expected loss, was able to be included amongst the top rotations in the South Valley. This resulted in the soybean – winter wheat rotation ($55.17/ac) ranked third behind the soybean - dry edible bean ($129.17/ac) and the corn - soybean ($61.27/ac) rotations; even though winter wheat

[a] Winter wheat was not grown for variety trials in the North Valley region of North Dakota and was not able to be compared

revenue in the South Valley turned in a loss (-$40.25/ac), they were heavily outweighed when paired with the very profitable soybeans ($148.48/ac). This result for the South Valley region is also due to the limited variety of crops with available trial data. Planting winter wheat after soybeans also requires an early soybean harvest to allow the winter wheat enough time to develop its crown before winter. While this may be possible in parts of the South Valley with ideal weather conditions, it cannot be reliably planned.

Table 1.4: Annual average revenues per acre ($)

Crop	North Central	Northeast	Northwest	Southwest	East Central	South Valley	Southeast	South Central
Winter Wheat	130.13	87.39	75.56	34.98	(10.70)	(40.25)	(41.07)	(44.79)
Corn	39.32	32.05	(131.41)	-	55.22	(38.97)	83.87	-
Soybeans	102.78	175.61	(40.64)	(6.87)	168.70	148.48	133.65	50.60
Spring Wheat	86.86	98.21	42.22	-	42.38	-	62.61	5.83
Durum	114.11	137.78	70.63	-	83.68	-	(57.04)	117.77
DEB	145.64	378.77	(95.97)	-	183.82	104.58	-	-
Canola	304.69	146.27	9.63	-	-	-	-	-
Sunflower[a]	191.95	269.49	67.41	-	92.66	-	-	-

[a] Values listed are for sunflowers grown for confection, which outperformed oil sunflowers in all regions.

While winter wheat was the top performing crop in the Northwest region, declining farming importance with the regional oil boom is detrimental to the expansion of winter wheat in the Northwest. Not only is land being bought for oil production but the oil waste pits left behind have a harmful effect on wildlife. The greatest concern comes when oil production has ceased in the area and the oil waste pits remain open for up to a year before being closed (Ramirez 2009). Birds visit the fluid-filled pits as often resemble water sources but may be killed by oil exposure (Trail 2006). However, even if these issues are resolved, winter wheat will likely have to wait until oil production has stopped to make a realistic push for acreage in the region.

Sugar beet planting is largely confined to the North Valley, South Valley, and Northeast regions of North Dakota due to requiring close proximity to processing facilities; however, trial data was not available in these regions. Sugar beet revenues, where data was available, appeared grossly overstated (approximately an order of magnitude greater than other crop revenues). This could be the result of limited number of observations, planting quotas, the adjustment made to loan prices, or inconsistencies caused by the use of a crop budget report from a different source – Crystal Sugar budgeting data (Bangsund et al 2012) and not NDSU Extension Service as was used for the other crops – and not an indication of an outright financial advantage. The assumption that the two sources are based on similar farm management operations is probably incorrect, which led to inaccurate revenue projections.

Conclusions & Observations

The opportunity to plant winter wheat will become more inviting as breeding efforts yield results in the coming decades; however, is there something that can be done sooner? Converting acres normally planted to spring-seeded crops into winter wheat now would provide easily implemented returns to duck nesting habitat – switching a spring-seeded crop for no-till winter wheat one in four years could provide an additional 0.12 ducks/ac/year (0.08 ducks/ac/year for one in six years converted to winter wheat). Switching to winter wheat would also allow for farmers to shift some of the labor and machinery to the fall, easing some of the demand in spring.

As nesting habitat in the PPR continues to be replaced with cropland, winter wheat presents an opportunity to compensate for this land use transition by reducing field machinery use in early spring. The Northwest region demonstrates this potential through two routes. As it resides within the PPR, it sees an abundance of ducks attempting to nest in the region; the Northwest region also has winter wheat as the top revenue per acre crop with NDSU VTR data. In the adjacent North Central region, also within the PPR, winter wheat revenue per acre resides in the middle of the pack but could see breeding efforts soon improve its standing. The justification to farmers will have to rely upon financial benefits which have this research has shown the potential for. Support for winter wheat could also be driven through crop policy or the willingness for bird hunters to pay to hunt near winter wheat with knowledge of the advantages it has for nesting habitat. Private organizations, like Ducks Unlimited, can continue or begin investing resources and time to research, lobby for, or spread information on the benefits of planting winter wheat, namely increased duck nesting habitat and improving crop diversity to reduce risk.

This study reveals two regions in North Dakota that could provide good financial returns to producers for planting winter wheat, thereby improving duck nesting habitat in the PPR. Several regions in North Dakota already boast winter wheat revenues comparable to other crops using data from the NDSU variety trials. Fitting winter wheat into a rotation may be the more challenging issue as winter wheat must follow an early harvest crop, typically spring wheat, in order to establish a stand before winter. The ability to plant winter wheat after soybeans would help to improve the outlook by adding rotation flexibility and reduce the risk of disease present when following spring wheat.

As we were unable to find a suitable experimental research farm with rotation data that produced significant influences of rotation upon crop yield, our research relied upon NDSU Extension Services' Performance Variety Trials for yield data. Future studies would be aided by data where rotational influences could be derived and included in the analysis. Long-term continuation of work at the CCSP would be a boon to such efforts.

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CHAPTER 2: ECONOMIC FACTORS INFLUENCING LAND-USE CONVERSION FROM IDLE/CRP TO CROPLAND: CASS COUNTY, ND

Abstract

As crop prices rise across the nation, and financial incentives for enrolling land in CRP stagnate, land-use conversion from CRP to crop production is increasing. Understanding the relationships between land choice factors in Cass County, ND is the intent of this study. As CRP contracts expire in Cass County, many of these acres will likely not be re-enrolled, but rather converted into cropland. By examining how decision factors influence farmers' land-use choices, this study aims to predict how the acreage will be allocated and the potential repercussions it will have. While there have been similar studies done incorporating land-use change and CRP, the inclusion of satellite imagery and economic factors has been limited. This research converts the USDA NASS Cropland Data Layer (CDL) into field plots to limit the computational workload on performing a logistic regression on land-use choice parameters. The regression uses operating revenue and weather data as decision factors with the land-use of the parcel as the dependent variable. The relative effect of operating revenue and previous land-use was consistent across both CATMOD and MDC procedures in SAS. Previous years' land-use was of far greater importance in determining subsequent land-use than operating revenue or weather variables.

Introduction

The choice to enroll land in CRP has become less enticing as crop returns increase, and as CRP rental payments lag behind the general price level in agriculture. As crop prices rise across the United States, and specifically North Dakota, the financial incentive for enrolling in the Conservation Reserve Program (CRP) has failed to maintain enrollment levels. Though CRP enrollment for Cass County – and North Dakota at large – has increased by 36% since 1998, enrollment has decreased by 16% since 2006. Another 11,049 of the 27,524 acres on contract are set to expire from 2013 through 2015 (USDA FSA, 2014). The future of CRP enrollment may depend on a number of factors that affect the profitability of various management decisions at the farm level, some of which have been quantified in previous research, while others have not. The future of the CRP is of interest because reduced enrollment will reduce the valuable environmental benefits associated with this program, including water quality and wildlife habitat, among others (Johnson & Schwartz, 1993) (Marton, Fennessy, & Craft, 2013) (McCoy, Ryan, Kurzejeski, & Burger, 1999) (Murray & Best, 2014).

Secchi et al. (2009) used data from Iowa to estimate the effects of biofuels production on CRP enrollment via increasing market prices for corn and soybeans, and modeled environmental impacts of reduced CRP enrollment under various corn price scenarios. Their findings suggest that maintaining current environmental quality will require increased spending levels and more effective targeting of the most environmentally sensitive lands. Secchi et al. (2011) constructed cost of production budgets and crop price scenarios to predict farmers' choices of crop rotation in Iowa, both for land in current production and land returning to agricultural use after CRP expiration. Anticipated changes include intensification of corn production through increased adoption of continuous corn rotations, as well as extended scope of corn production through conversion of lands currently enrolled in CRP. These changes in intensity and scope are predicted to substantially increase nitrogen and sediment losses that will deteriorate surface water quality. Environmental concerns are not unique to Iowa. While factors involved in farmer land use choice in Iowa are likely similar to Cass County (ND), there are certainly agricultural, climatic and economic differences between the regions.

Research applying satellite imagery to economics models of land-use change modeling has been limited. As outlined by Rashford et al. (2012), there are a number of hurdles to pass in regard to being able to handle databases like the cropland data layer (CDL) produced by USDA NASS. As the CDL's pixels represent 30 meter by 30 meter plots, the main obstacle is the computational time it takes to fit choice models to the high number of observations. Rashford et al. (2012) dealt with the computational limits by grouping the choices into two categories, grassland and cropland. The aggregation of the CDL classes into two categories was not an option for our study though, as the binary binning would not have allowed for a relation to specific rotation choices. As a binomial model also reduces the number of choices, the number of wholly unique observations (i.e. having no other replications of a specific combination of all variables) is also reduced. While these differences allow for reduced computational time, they also limit the breadth of land-use choice analysis. Secchi et al. (2011) make use of the CDL. However, their land use change model is based on budget and crop price scenarios alone, rather than the response of historical land use choices to economic conditions. This research develops models and estimates results showing how land use decisions respond to changing conditions, rather than assuming that farmers make their choices based only on a budgeting exercise.

This study estimates a discrete choice model utilizing more than a decade of crop choice observations to economic conditions, managing the computational restrictions outlined by Rashford et al. (2012) by converting the original rasters into polygon layers representing fields. The conversion from 900 m^2 plots to fields on the scale 6.9 km^2 reduces the number of annual observations from 4.8 million to 8,050; however, it requires additional data in the form of parcel data. Grouping the raster files into parcels also compensates for some spatial dependency, as each field is planted into a crop and the CDL is not accurate enough to correctly identify the crop on all of the pixels that represent a field. Some spatial dependency does still exist due to geography, soil, presence of market infrastructure (e.g. processing facilities for sugarbeets), and/or climate.

The goals of this research were to: [1] use satellite imagery to model and predict land-use decisions, [2] determine the dominant influences on crop choice in Cass County, ND, and [3] generate an output ready to be used in estimating effects in Cass County of expiring CRP on environmental quality, wildlife habitat, and cropping patterns. This research will also show the potential repercussions for land-use change as crop prices and CRP rental payments vary.

Methodology

Data

Cass County lies on the border of North Dakota and Minnesota along the Red River. It is also on the edge of the Prairie Pothole Region. The county seat – Fargo – is also the largest city in North Dakota. The main reason for selecting Cass County for this research is the availability of quality property parcel data. Cass County represents 1768 mi^2 out of the state's 70,700 mi^2.

This study used publicly available property parcel data from Cass County's website, Web Soil Survey Geographic Database (SSURGO) soil data, annual growing degree day (GDD) data from Weatherunderground, NASS Quick Stats' crop price & yield data, CRP payment data from Environmental Working Group (EWG), CRP acreage data from the Farm Service Agency (FSA) and the 16 USDA NASS CDLs for years 1997 through 2012. North Dakota Agricultural Weather Network (NDAWN) was also accessed to collect weather data for annual average temperature, total rainfall, and Potential Evapotranspiration (PET) from NDSU campus. Means and standard deviations between annual values for weather and soil factors are reported in Table 2.1. The CDL is a raster, geo-referenced, crop-specific land cover data layer. The CDLs for 1997 through 2005 have ground resolutions of 900 meters^2. These CDLs are produced using satellite imagery from the Landsat sensor collected during their respective growing seasons. The CDLs from 2006 to 2009 have ground resolutions of 3136 meters^2. The CDLs after 2009 have ground resolutions of 900 meters^2. These CDLs are produced using satellite imagery from the Landsat 5 TM sensor, Landsat 7 ETM+ sensor, and the Indian Remote Sensing RESOURCESAT-1 (IRS-P6) AWiFS collected during their respective growing season. After limiting the CDL extent to Cass County, ND, the number of observations for each year's data layer was approximately 4.8 million.

Table 2.1: Weather and soil factors

	GDD	**Precipitation (inches)**	**Temperature (°F)**	**PET (inch/year)**	**Crop Productivity Index**
Mean	2394.25	19.91	42.24	49.50	52.16
SD	278.25	5.67	1.73	3.18	39.15

There were 128,000 total observations compiled over the 16 years. The frequency of each land use code is reported in Table 2.2. A single observation equates to having one field in one year in the respective land use. A second year or second plot in the same year would result in a second observation.

Model Development

Cass County Parcel data was used in this study to group raw raster pixels into field-scale plots. This was necessary in order to improve the accuracy of identifying crop rotations. Converting to polygons also reduced the number of individual observations for fitting and modeling of all 16 years from approximately 77.8 million to 128,230 (~0.2%). The reduction in observations greatly reduced the computer processing time, making the fitting durations more reasonable (typically several minutes instead of hours or potentially days). Limiting the time spent estimating the model allowed for adjustments to be made without wasting hours in computation. Converting to polygons also compensates for some spatial dependency. Since the CDL is not able to consistently identify crops correctly, many fields do not display a single uniform crop as would be expected. Grouping the raster files into parcel polygons ensures there is only one crop represented per field per year.

Table 2.2: Code frequencies developed from SAS

Crop	Frequency	Percent
Alfalfa	248	0.19
Barley	1003	0.78
Canola	174	0.14
Corn	18338	14.30
Dry Bean	1430	1.12
Durum	393	0.31
Flaxseed	38	0.03
Grassland/Pasture/CRP/Idle	10163	8.71
Oats	44	0.03
Potatoes	47	0.04
Small Grains	94	0.07
Soybeans	54149	42.23
Spring Wheat	35774	27.90
Sugar Beets	1958	1.53
Sunflower	1545	1.20
Water/Wetlands/Wooded	2684	2.09
Winter Wheat	148	0.12

As financial incentives drive much of the agricultural industry and in turn cropping choices, including price received data was essential for a successful the land-use choice model. To better understand the relationship between crops and CRP enrollment, the financial incentive for enrolling in CRP was estimated using an average payment per acre for Cass County. Crop prices and CRP payments were adjusted to 2012 values using the Consumer Price Index (CPI) from the United States Bureau of Labor Statistics. Crop prices were then multiplied by respective yield for each year to determine the estimated operating revenue for each crop and year. Means and standard deviations for these values are presented in Table 2.3. These values were lagged one year to more accurately represent the decision factor available to farmers at planting.

Crop choices are heavily influenced not only by economic data but also by the regional climate. Weather data for Cass County was retrieved from NDAWN and Weatherunderground. Specific data acquired for model estimation included annual average temperature, total growing degree days (GDD), total precipitation, and Potential Evapotranspiration (PET). Since cropping choices are typically made before the growing season's weather is known, one year lags of these variables were created for model inclusion. However, there are also some cases when extreme spring weather can dictate which crops are even able to be planted.

ArcGIS® was consistently used throughout data preparation. Before rasters could be converted into polygon shapefiles, the Cass County Property Parcel (CCPP) shapefile had to be modified for use in this study. First, the CCPP shapefile was dissolved to split parcels that contained multiple fields. The file was also split manually using the edit tool to break parcels where fields were divided up more than ownership boundaries. The final step in preparing the CCPP shapefile was creating a unique identification number for each polygon. Raster files, one for each year 1997 – 2012, were then converted into polygon shapefiles with the *Raster to Polygon* tool. Through the *Union* tool applied to the new polygon shapefile with the CCPP shapefile, these polygons gain the identification number and field layouts from the parcel data. Within the attribute tables of these unions, a new column was generated using *Summarize* on the identifier column to output the maximum area polygon within each parcel. These maximum area output tables were then joined with their respective union shapefiles to delete all polygons not representing the maximum area within a parcel. This step was critical in ensuring that fields corresponded to a single crop per year. The shapefiles were then combined using the *Spatial Join* tool to create a single shapefile that included the annual crop codes for all observation years – 1997 through 2012. A raster with soil classification data from SSURGO was included using the same method as the CDL rasters (Soil Survey Staff 2013). Of specific interest to this study is the crop productivity index from SSURGO that is linked to the soil type code. However, not all cropped soil types have a crop productivity index, which diminishes this variable's value for analysis.

Table 2.3: Economic factors based on 2012 adjusted CPI factors

	Corn ($/ac)	Soybean ($/ac)	Spring Wheat ($/ac)	Winter Wheat ($/ac)	Canola ($/ac)	Dry Bean ($/ac)	Flaxseed ($/ac)	Sunflower ($/ac)	CRP ($/ac)
Mean	400.54	267.77	200.51	199.53	229.08	367.37	171.61	236.67	67.86
SD	181.91	91.03	85.38	90.97	90.97	109.93	62.31	98.91	7.39

After the spatial joins were completed, the attribute table was exported for analysis. Before analyzing the data in SAS, it first had to have errors that had propagated through the processing fixed. Since the CDL is only about 80% accurate, there are errors in land-use identification that surface during data inspection. In many cases, the change was made from rotations identified as soy-on-soy to match the rotation present for the rest of the years on that plot. There were also occasions when a parcel was classified as an urban land-use class for only a year or two and then returned to agriculture. As developing land is expensive and generally destroys the ability to produce crops on it in the future, these situations were assumed to be classification errors. The observations were inspected in ArcGIS® to determine if they were in potential development areas. If so, they were removed from the dataset. In the cases where they did not appear to be part of developments, a continuation of the crop rotation for the parcel was assumed in place of the urban classification. There were also observations that only had a few years of agricultural classification; these were removed from the dataset as well since there was no discernible rotation present.

The SAS CATMOD procedure (SAS Institute Inc., 1985), modified for logistic regression, was used to determine the associations of the 20 codes from the CDL data with the independent variables presented earlier. Once the table had been cleaned and trimmed of incorrect data, there were 8,050 plots with 16 years of land-use classification codes for each. This data was represented by 1353 unique populations. The one and two year lagged crop codes were the only independent categorical variables used for modeling. Independent factors for modeling included: operating revenue for corn, soybeans, spring wheat, winter wheat, durum, sunflowers, hay, barley, dry edible beans & sugar beets, payment for CRP enrollment, GDD, total rainfall, average temperature and crop productivity index.

The regression model is given by the equation:

$$\log\left(\frac{\pi_{kc}}{\pi_{kr}}\right) = \varepsilon_{ct} + \beta_{l1}L_{t-1} + \beta_{l2}L_{t-2} + \beta_{c}x_{k,t-1} \tag{6}$$

here π is the probability that a plot within population k prefers land use c, $c \neq r$, and land use r is reference – alfalfa. Year is denoted by t (t-1 and t-2 being the one and two year lags, respectively); ε is the intercept; i refers to the decision variable being specified; x denotes the vector of explanatory variables used to predict land use choice; the β's are the respective regression parameters to be determined from PROC CATMOD in SAS. Since the tables containing the SAS output tables are quite large, only limited results providing interest or insight will be included in our discussion.

An extension of the binomial logit model, the multinomial logit (MNL) model applies to scenarios with more than two distinct outcomes. Since our data includes 19 distinct outcomes, it was necessary to use MNL rather than the binomial version. Other regression techniques that can be applied to greater than two outcomes include the nested logit and the multinomial probit. The case could be made for using the nested logit model instead of MNL since a lower nest classification for crops/non-crops would make sense; however, if we are assuming that farmer is only interested in the financial capabilities of the outcome, the distinction between crop and non-crop land use becomes moot.

An equation is defined for each alternative (land use choice) and estimated simultaneously, to ensure consistency, using SAS's CATMOD procedure. This generates n-1 equations, where n is the number of alternatives, for the generalized logits of the alternatives with respect to the n^{th} (alfalfa land use); CATMOD derives parameter estimates simultaneously, to ensure consistency, using maximum likelihood estimation (other estimation methods are available; however, the default maximum likelihood option was used).

Instead of using each crop's net revenue per acre, which would have required finding a source that included projected budgets for all crops and each year from 1997 through 2012, operating revenues were included into the model. While operating revenues do not take into account the cost of growing crops, it does serve as a means to incorporate an increase in price received for crops and/or an increase in potential yield for a crop. Even though this study was unable to incorporate planting costs due to the unavailability of data, including a form of crop revenue was necessary to understand farmer land-use choice. Operating revenues allow for the incorporation of yield on-top of price while admittedly remaining incomplete by lacking planting and harvesting costs. The expectation is for operating revenue to be positively correlated with the log-likelihood of a crop as an increase in potential revenue should encourage planting the respective crop.

The most direct influence in convincing farmers to convert crops to CRP is the financial incentive to do so. Farmers can receive payments for converting acreage out of cropland and into long-term restored habitat. These CRP payment values for Cass County were retrieved from

EWG website (EWG 2013) and converted into per acre values using enrolled acreage in CRP for Cass County from the FSA website (USDA FSA 2013). This variable is expected to decrease probability of crops (negatively correlated) and increase pasture/idle/grassland (positively correlated).

A number of land quality factors have been included in the literature to aid in land use choice modeling. Data from SSURGO (Soil Survey Staff 2013), which included a crop productivity index variable, was used to assess the influence of land quality on farmers' land use choice. Unfortunately, not all soils identified in Cass County had a crop productivity value included. These cases were still included in the analysis but did not have a value included for the regression. As such, the significance of the crop productivity value for the soil was negatively impacted and was dropped from the model.

As weather has a large effect on crop success, it is expected to influence what crops farmers decide to (or not to) plant. Decisions are made based on which crops have a better opportunity to avoid risk or see improved yield expectations. One year lagged weather variables were the basis for this decision factor since crop season forecasts have generally been unable to accurately predict year-long climate conditions. If the year previous was drier and warmer (potentially leaving less moisture in the ground for spring crops), a more drought resistant crop may be expected to have an increased chance of being planted in the subsequent year.

The NASS CDL contained a large number of codes, many of which were unnecessary for our study (no or minimal observations) or divided the observations into too specific of categories that were grouped together for this study. Codes that were combined into new categories included: open water, water, wetlands and wooded and pasture/range/CRP, grassland herbaceous, fallow/idle and pasture/hay.

The MDC regression was added to look at another possible way to analyze the data set. While the MDC procedure works very similar to the CATMOD procedure, it differs in one important way. Data input formatting for CATMOD takes tables in the wide-format where MDC accepts only long-formatted tables. The conversion of the table to long-format allowed for each crops' operating revenues to be grouped into one column since each alternative land use choice is listed for each observation. The one year lagged value for that crop's respective operating revenue was inserted into that field. Therefore; instead of having each crop's operating revenue as decision variables, it was a single operating revenue variable that contained all alternatives' values. This greatly reduced the complexity of the model and thus the computational time as well.

Results

CATMOD

Fitting the logistic regression yielded estimates of the impacts of the decision factors on the dependent variable, land-use code. Iterations of the model were run until each of the decision variables was significant to at least the $\alpha < 0.10$ level. The flax and durum operating revenues were removed, as well as total rainfall, average temperature, and PET. Since these variables did not statistically affect the model fit, including them would have potentially biased the significant factors as well as unnecessarily reduced the degrees of freedom of the regression. Due to the dominance in counts for corn, soybeans, spring wheat, fallow/idle, and grassland/pasture/CRP – making up 92.4% of all observations – they represented the most important land use choices to investigate.

Previous models had been run without combining similar land use codes, but failed to be very accurate or converge at all in some cases. While there was slight success in running models in this fashion using just one year lagged code values, the inability for the model to successfully include two year lagged land use codes led to land use code grouping. See Appendix C2 for CATMOD regression maximum likelihood analysis of variance; other regression fit data available upon request (approximately 50MB of table data).

The returned β values for categorical factors indicate change in likelihood for a decision factor using alfalfa land as the basis for comparison. For example: in Table 2.4 the log-likelihood that soybeans will follow corn is 6.30 times greater than alfalfa following corn and the log-likelihood of dry edible beans following corn is 10.25 times greater than alfalfa following corn – outweighing that of soybeans. This result was unexpected and not corroborated in the data; it may be the result of high volatility in dry edible bean operating revenue.

The returned β values for non-categorical factors indicate the responses to a one unit increase of the respective decision variable. These responses are measured in increases or decreases in plots planted. In the case of CRP and crop operating revenues, these responses show the increase or decrease expected for a one dollar increase in payment or revenue. For example: in Table 2.5 an increase in corn operating revenue by one dollar increased the log-likelihood of corn in the following year by 0.016 times over alfalfa land use.

Through the CATMOD fit, dry edible beans appears to be a very likely pairing with corn in Cass County; however, in reviewing the CDL and NASS Cass County yield data, there may be an issue in discerning dry edible beans from soybeans within the modeling procedure. As dry beans is only planted 1.12% of the time and requires different equipment than other crops, it would be an unlikely candidate for a farmer to try on a whim. It may also be an artifact of the effect of the price volatility seen for dry edible beans. In reviewing the raw data, the beta value for one-year lagged corn indicating a large increase in the log-likelihood of dry edible beans was deemed to be inaccurate.

Table 2.4: One Year Lagged Land-Use Choice Regression β Values

	Log-Likelihood of Crop to Follow				
Previous Year Land Use	**Corn (sd)**	**Soybeans (sd)**	**Dry Beans (sd)**	**Winter Wheat (sd)**	**Grassland/Pasture/CRP (sd)**
Corn	-2.33	6.30	10.25	0.59	-0.90
	(11.30)	(10.93)	(15.13)	(16.01)	(11.17)
Soybeans	2.01	-5.21	-0.35	0.51	-0.35
	(8.41)	(7.96)	(11.49)	(11.56)	(8.25)
Dry Beans	2.09	-2.31	-0.27	0.52	-0.33
	(8.50)	(8.05)	(11.60)	(11.68)	(8.34)
Spring Wheat	-0.91	5.47	1.83	0.62	-0.36
	(8.66)	(8.21)	(11.76)	(11.91)	(8.50)
Wetlands/Water/Wooded	-1.36	-3.75	-0.29	0.51	0.98
	(8.47)	(8.01)	(11.56)	(11.63)	(8.30)
Grassland/Pasture/CRP	-0.43	-2.47	-0.35	0.46	4.40
	(8.41)	(7.96)	(11.49)	(11.56)	(8.25)
Winter Wheat	-0.70	4.07	-0.99	-0.11	-1.22
	(23.71)	(23.38)	(39.70)	(42.05)	(25.02)

Table 2.5: Two Year Lagged Land-Use Choice Regression β Values

	Log-Likelihood of Crop to be Planted in Two Years				
Two Year Previous Land Use	**Corn (sd)**	**Soybeans (sd)**	**Dry Beans (sd)**	**Winter Wheat (sd)**	**Grassland/Pasture/CRP (sd)**
Corn	6.36	0.55	0.45	0.24	-0.23
	(0.93)	(1.26)	(2.13)	(2.20)	(1.29)
Soybeans	0.12	1.13	0.26	0.21	-0.16
	(0.89)	(0.88)	(1.43)	(1.44)	(0.91)
Dry Beans	0.31	0.20	1.36	0.25	-0.31
	(1.63)	(1.63)	(2.09)	(2.37)	(1.64)
Spring Wheat	-2.16	0.82	0.37	0.25	-0.49
	(1.01)	(0.98)	(1.57)	(1.60)	(1.00)
Wetlands/Water/Wooded	-0.79	-1.57	0.25	0.20	0.90
	(1.20)	(1.21)	(1.88)	(1.89)	(1.21)
Grassland/Pasture/CRP	-0.63	-0.95	0.19	0.16	3.37
	(0.93)	(0.93)	(1.49)	(1.51)	(0.95)
Winter Wheat	0.73	-0.14	0.34	0.55	-0.40
	(2.08)	(2.04)	(4.38)	(3.99)	(2.40)

MDC

The results table for procedure MDC is much simpler and can be included here in its entirety. Shown in Table 2.8 are the parameter estimate results from the logistic regression performed using MDC. Of particular note is the ability to relate the influences of previous crop choices with operating revenue. This is accomplished by combining the operating revenues for each crop into one decision variable, and the same for land use crop choice alternatives. Last year's crop choice is the only negative parameter. This should come as no surprise since many crops experience disadvantages to being continuously cropped. Two and three year lags were positive and show the prevalence of two and three year crop rotations. Two year rotations work to lower the parameter of the three year lag due to the lower likelihood for planting the same crop in back-to-back years.

Table 2.6: Lagged operating revenues regression β values

Last Year Operating Revenue	Corn (sd)	Soybeans (sd)	Dry Beans (sd)	Winter Wheat (sd)	Spring Wheat (sd)	Grassland/Pasture /CRP (sd)
Corn	0.0161 (0.0177)	0.0211 (0.0172)	0.0003	0.0025	-0.0016	-0.0417
Soybean	-0.0424 (0.0302)	-0.0281 (0.0294)	-0.0001	-0.0042	0.0031	0.0829
Spring Wheat	-0.0453 (0.0208)	0.0637 (0.0203)	-0.0049	-0.0019	0.0056	-0.0212
Durum	0.0216 (0.0207)	0.0034 (0.0200)	0.0052	0.0037	-0.0102	-0.0357
Winter Wheat	0.0418 (0.0246)	-0.0319 (0.0241)	-0.0069	-0.0001	0.0131	-0.0038
Dry Beans	-0.0087 (0.0086)	0.0031 (0.0083)	-0.0005	-0.0005	0.0010	0.0084
Barley	0.0233 (0.0137)	-0.0195 (0.0132)	0.0038	0.0018	0.0063	-0.0092
Sunflower Oil	-0.0264 (0.0262)	-0.0506 (0.0255)	0.0048	-0.0041	-0.0127	0.0803
Forage	0.1160 (0.0647)	0.0443 (0.0635)	-0.0155	0.0072	0.0327	-0.1687

Table 2.7: Other decision factors regression β values

Lagged Variable	Log-Likelihood of Crop to Follow Corn (sd)	Soybeans (sd)	Dry Beans (sd)	Winter Wheat (sd)	Spring Wheat (sd)	Fallow/Idle (sd)	Grassland/Pasture /CRP (sd)
CRP $/acre	-0.0931 (0.1293)	-0.1538 (0.1285)	0.0305 (0.1775)	0.00831 (0.1823)	0.1845 (0.1284)	0.0329 (0.1397)	0.1292 (0.1286)
GDD	0.00396 (0.00531)	0.00374 (0.00525)	-0.00095 (0.00723)	-0.00018 (0.00749)	0.00243 (0.00525)	-0.00033 (0.0056)	-0.0110 (0.00526)

Table 2.8: MDC parameter estimates

Parameter	Parameter Estimates DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Oprev	1	0.0005	$1.4E^{-5}$	36.27	<.0001
choice_1	1	-0.7061	0.0128	-54.97	<.0001
choice_2	1	3.2616	0.0071	460.32	<.0001
choice_3	1	2.2550	0.0112	200.95	<.0001

Conclusions

Overcoming the computational limitations involved in applying satellite imagery data is the main obstacle in the way of vastly improved empirical models of CRP and land-use conversion. While the technique applied in this study is not feasible when applied to areas much larger than Cass County, ND due to the amount of fine scale corrections involved, it may be an option for similar size or smaller study areas.

When considering the possible conversion of CRP acreage into corn production, Secchi et al’s (2011) study for the state of Iowa lends some insight into the environmental ramifications that may result. In estimating the environmental effects of cropland conversion, Secchi et al categorized land use into rotations (corn-soybean, continuous corn, 2+ years of continuous soybeans, corn-corn-soybeans, and 3+ years of continuous corn) or CRP land. In utilizing the Environmental Policy Integrated Climate (EPIC) model, Secchi et al. (2011) were able to simulate edge-of-field environmental impacts based on crop rotations, weather, soil, landscape, and management system information.

Utilizing the CATMOD and MDC procedures within SAS allowed for slightly different regression modeling. Both procedures showed the relatively stronger effect of previous plantings on future land-use choices over that of financial gains. This is likely due to farmers having experience with a particular rotation. Rather than risk trying a new rotation – with which they may have minimal experience – for a potentially larger profit, farmers prefer to stick with their current rotations. The differences between CATMOD and MDC allowed for CATMOD to compare different crops' operating revenues, while MDC was able to group together the effects different operating revenues and different lagged land uses.

There is potential for this technique to be improved upon and be used for larger study areas if accuracy at one or several level(s) is/are improved. As there is also quite a bit of influence on fields due to the individual owning the property, the inclusion of an owner identifier factor could be used to improve this study. Because there are many parcels where the same owner has multiple spelling variations on their name, and occasionally typos during data entry, including this information within this study was not possible due to time constraints.

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APPENDIX A: NET REVENUE TABLES

Table A1: North Central rotations

Rotation	Net Revenue
SW - Durum	$ 87.08
Corn - Soy	$ 69.40
SW - Sunflower	$ 110.30
SW - Soy	$ 83.26
SW - WW	$ 103.26
SW - DEB	$ 103.66
WW - Soy	$ 120.30
DW - Canola	$ 211.08
SW - Canola	$ 154.28
Soy - Canola	$ 205.35
SW - Barley - Canola	$ 139.21
SW - WW - DEB	$ 114.61
SW - WW - Soy	$ 102.37

Table A2: South Central rotations

Rotation	Net Revenue
SW - Durum	$ 66.02
SW - Barley	$ 36.83
SW - WW - Soy	$ 3.60
SW - WW	$ (16.73)
SW - Soy	$ 25.71
WW - Soy	$ 1.83
SW - Flaxseed	$ 40.08

Table A3: East Central rotations

Rotation	Net Revenue
SW - Durum	$ 57.07
Corn - Soy	$ 116.42
Soy - Sugar Beet	$ 267.78
SW - Sunflower	$ 57.18
SW - Soy	$ 102.11
SW - WW	$ 11.16
SW - DEB	$ 114.14
WW - Soy	$ 81.78
Corn - Soy - SW	$ 88.11
SW - Barley - Soy	$ 83.77
SW - WW - DEB	$ 73.03
SW - WW - Soy	$ 65.02

Table A4: Northeast rotations

Rotation	**Net Revenue**
SW - Durum	$ 108.66
Corn - Soy	$ 104.73
Corn - Soy - SW	$ 96.91
Corn - SW - DEB	$ 163.42
SW - WW - DEB	$ 145.23
SW - WW - Soy	$ 105.32
SW - Sunflower	$ 173.23
SW - Soy	$ 128.59
SW - WW	$ 87.67
DW - Canola	$ 134.48
SW - DEB	$ 228.37

Table A5: Southeast rotations

Rotation	**Net Revenue**
SW - Durum	$ (8.57)
Corn - Soy	$ 112.89
Corn - Soy - SW	$ 89.37
Soy - Sugar Beet	$ 453.50
SW - Soy	$ 86.65
WW - Soy	$ 2.05
SW - WW	$ (20.11)
SW - Barley	$ 35.00
Soy - SW - WW	$ 10.11

Table A6: North Valley rotations

Rotation	**Net Revenue**
WW - Soy	$ 121.62
Corn - Soy	$ 17.76
WW - DEB	$ 66.90
Corn - Soy - WW	$ 31.71
Corn - DEB	$ 162.55

Table A7: South Valley rotations

Rotation	**Net Revenue**
WW - Soy	$ 55.17
Corn - Soy	$ 61.27
WW - DEB	$ 34.75
Corn - Soy - WW	$ 27.76
Corn - DEB	$ 40.84

Table A8: Northwest rotations

Rotation	Net Revenue
SW - DW	$ 46.73
Corn - Soy	$ (80.13)
SW - Soy	$ 11.19
DW - Canola	$ 36.75
SW - WW	$ 64.51
SW - Barley	$ 37.62
SW - DEB	$ (7.31)
SW - WW - Soy	$ 49.74
SW - WW - DEB	$ 41.81

Table A9: Southwest rotation

Rotation	Net Revenue
WW - Soy	$ 16.62

APPENDIX B: STATISTICAL RESULTS

Table B1: Plm model fit

R plm Model Fit	
Statistic	**Value**
Total Sum of Squares	21812000
Residual Sum of Squares	10351000
R-Squared	0.52545
Adj. R-Squared	0.51768

Table B2: CATMOD maximum likelihood analysis of variance

Maximum Likelihood Analysis of Variance			
Source	**DF**	**Chi-Square**	**Pr>ChiSq**
Intercept	16	44.8	<.0001
CNAME_1	256	8737.91	<.0001
CNAME_2	272	6579.81	<.0001
lagGDD	16	659.26	<.0001
lagCRP	16	742	<.0001
lagCORN	16	221.58	<.0001
lagSOY	16	367.78	<.0001
lagSW	16	297.92	<.0001
lagDURUM	16	76.99	<.0001
lagWW	16	155.84	<.0001
lagBEANS	16	47.53	<.0001
lagBARLEY	16	135.59	<.0001
lagSUNOIL	16	547.45	<.0001
lagFORAGE	16	394.78	<.0001
Likelihood Ratio	2.00E+04	3177772.1	<.0001

Table B3: MDC model fit

Model Fit Summary	
Dependent Variable	Decision
Number of Observations	103753
Number of Cases	1763801
Log Likelihood	-173081
Log Likelihood Null (LogL(0))	-293954
Maximum Absolute Gradient	12.17238
Number of Iterations	10
Optimization Method	Dual Quasi-Newton
AIC	346171
Schwarz Criterion	346209

Table B4: MDC goodness-of-fit measures

Goodness-of-Fit Measures		
Measure	**Value**	**Formula**
Likelihood Ratio (R)	241746	2 * (LogL - LogL0)
Upper Bound of R (U)	587909	2 * LogL0
Aldrich-Nelson	0.6997	R / (R+N)
Cragg-Uhler 1	0.9027	1 - exp(-R/N)
Cragg-Uhler 2	0.9058	(1-exp(-R/N)) / (1-exp(-U/N))
Estrella	0.9503	1 - (1-R/U)^(U/N)
Adjusted Estrella	0.9503	1 - ((LogL-K)/LogL0)^(-2/N*LogL0)
McFadden's LRI	0.4112	R / U
Veall-Zimmermann	0.8232	(R * (U+N)) / (U * (R+N))

APPENDIX C: CUMULATIVE DISTRIBUTION FUNCTION GRAPHS

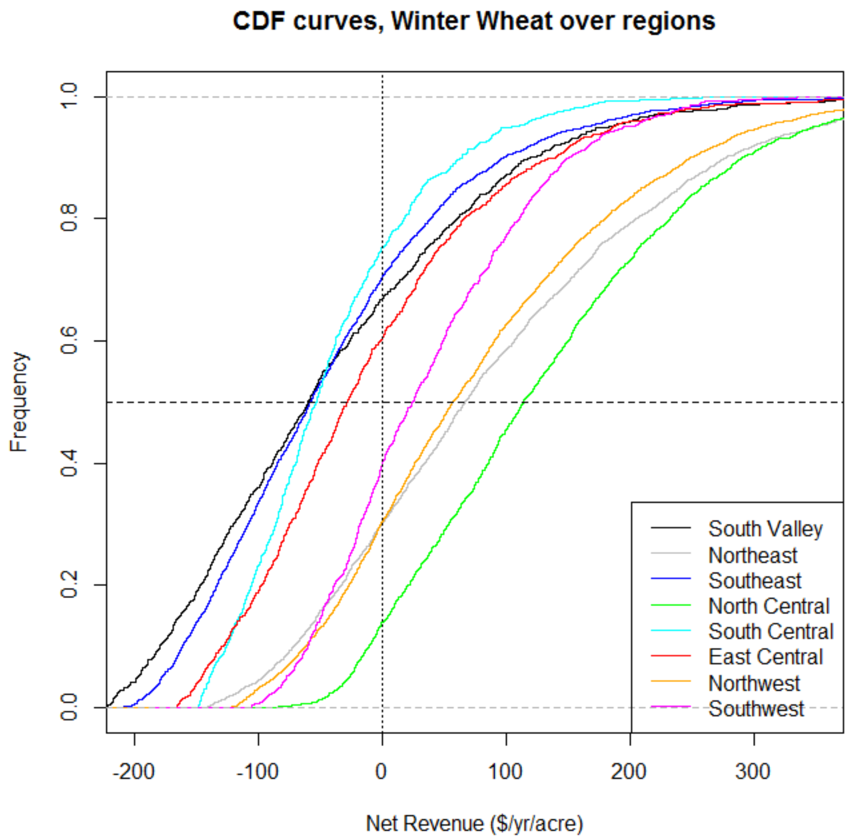

Figure C1: CDF curves for winter wheat, all regions.

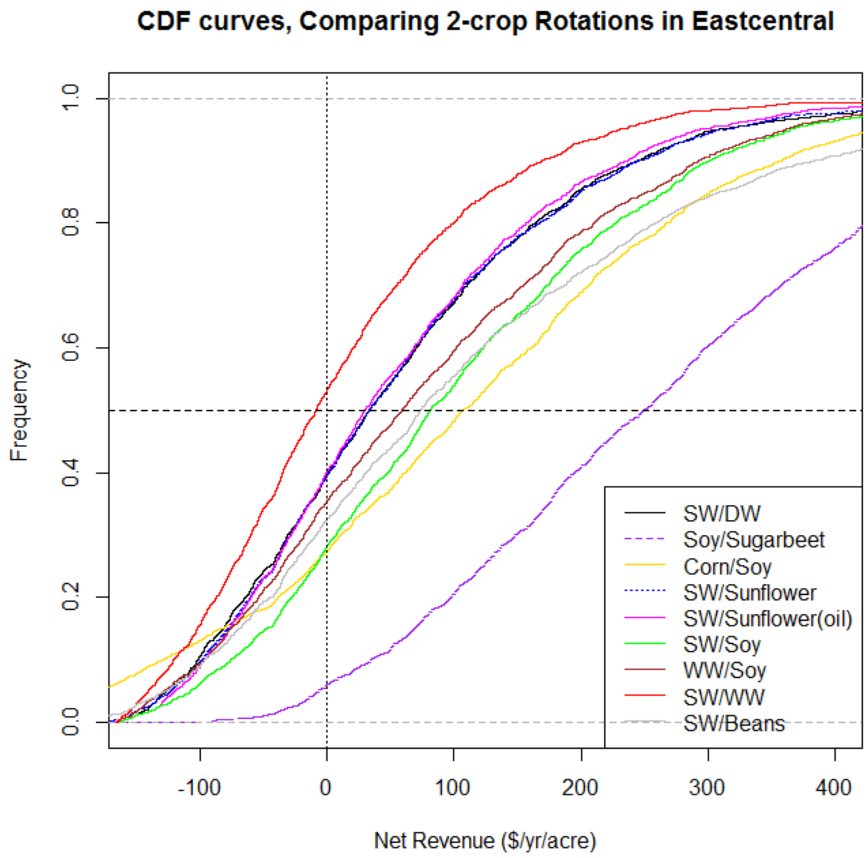

Figure C2: CDF curves for two-crop rotations, East Central region.

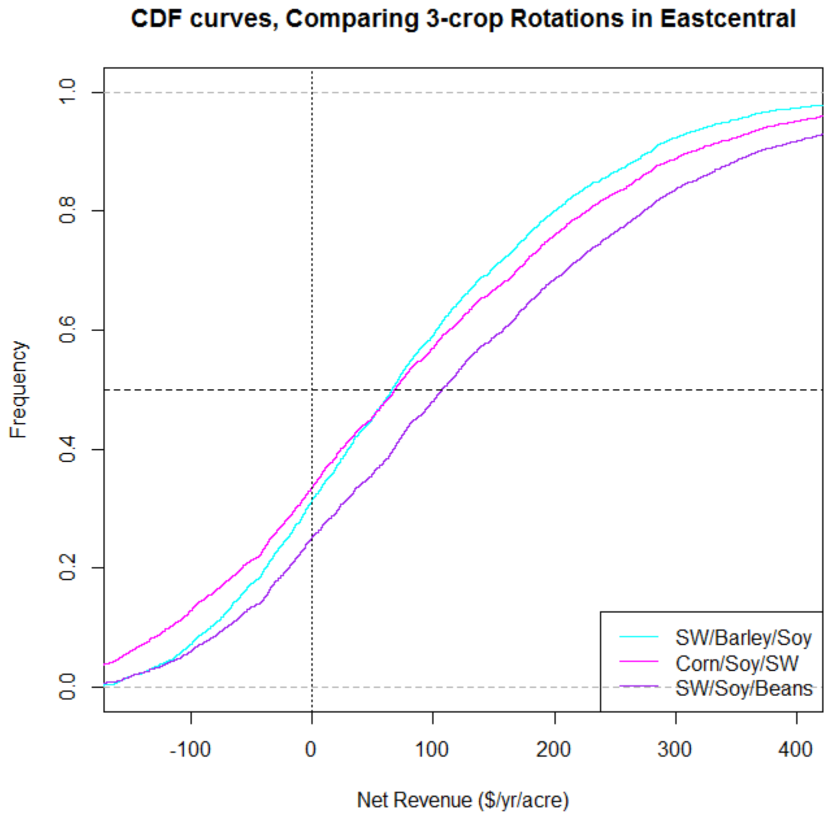

Figure C3: CDF Curves for three-crop rotations, East Central region.

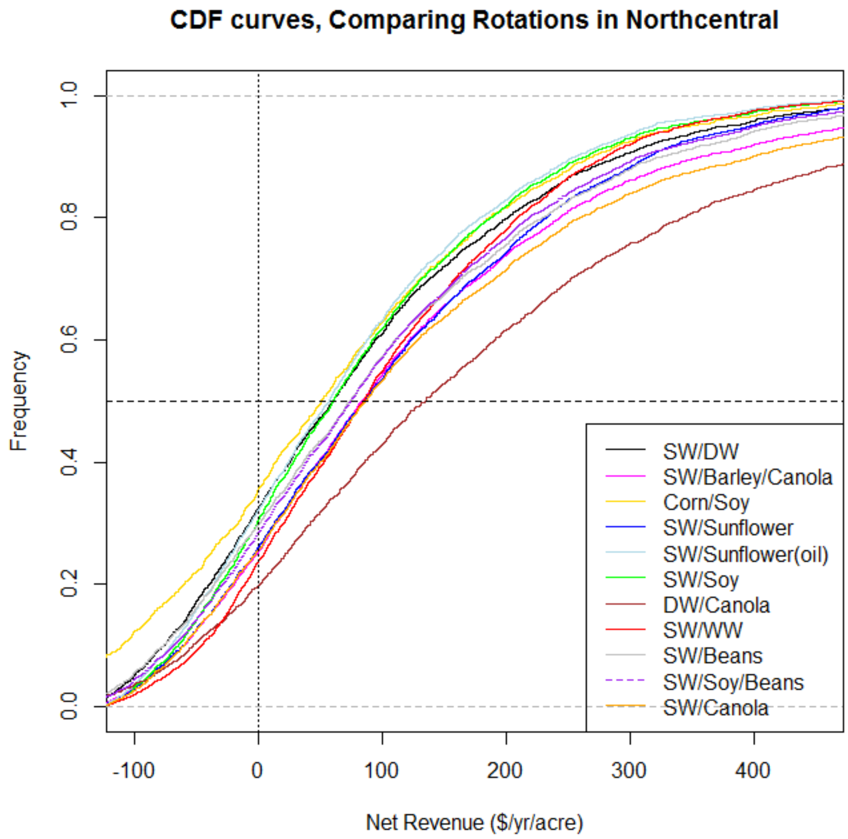

Figure C4: CDF Curves for crop rotation, North Central region.

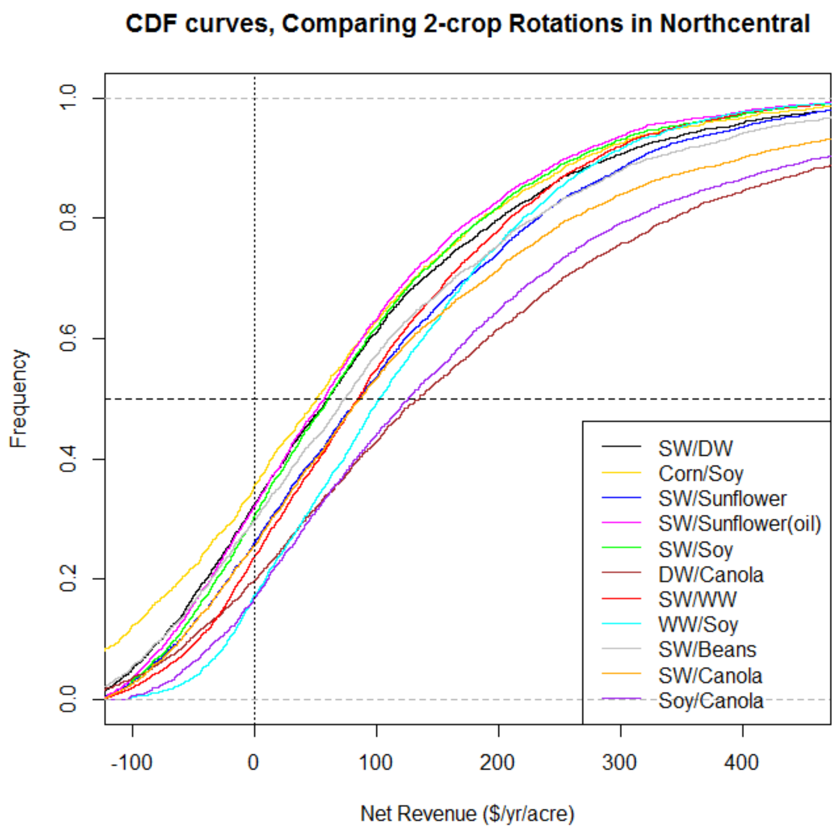

Figure C5: CDF curves for two-crop rotations, North Central region.

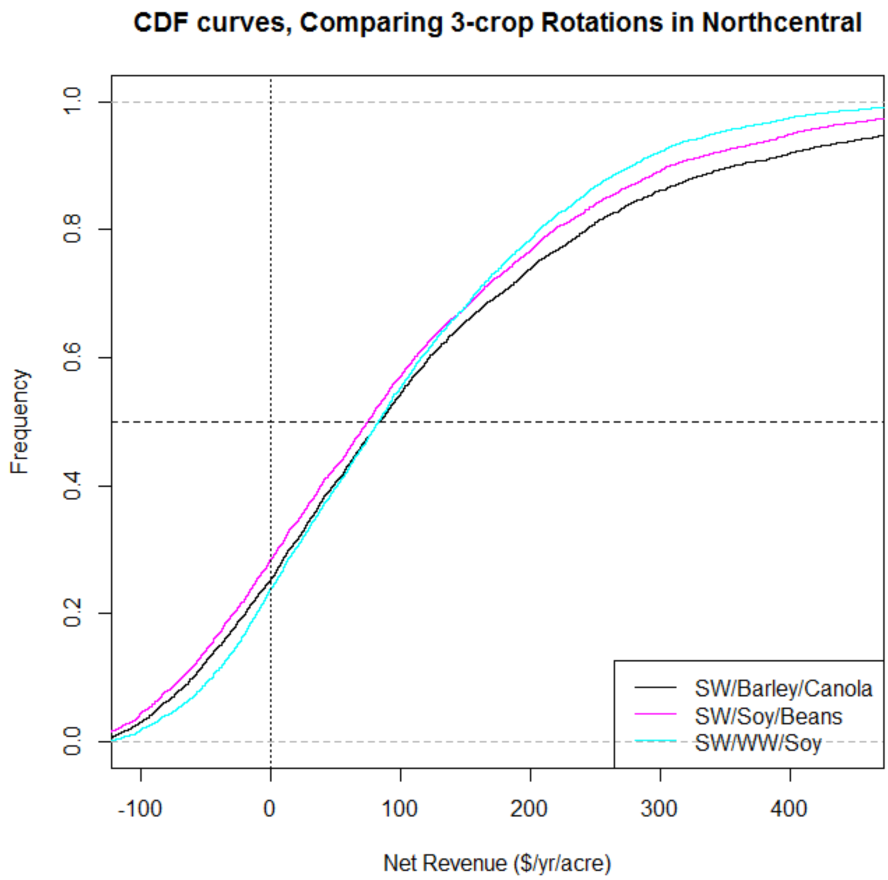

Figure C6: CDF curves for three-crop rotations, North Central region.

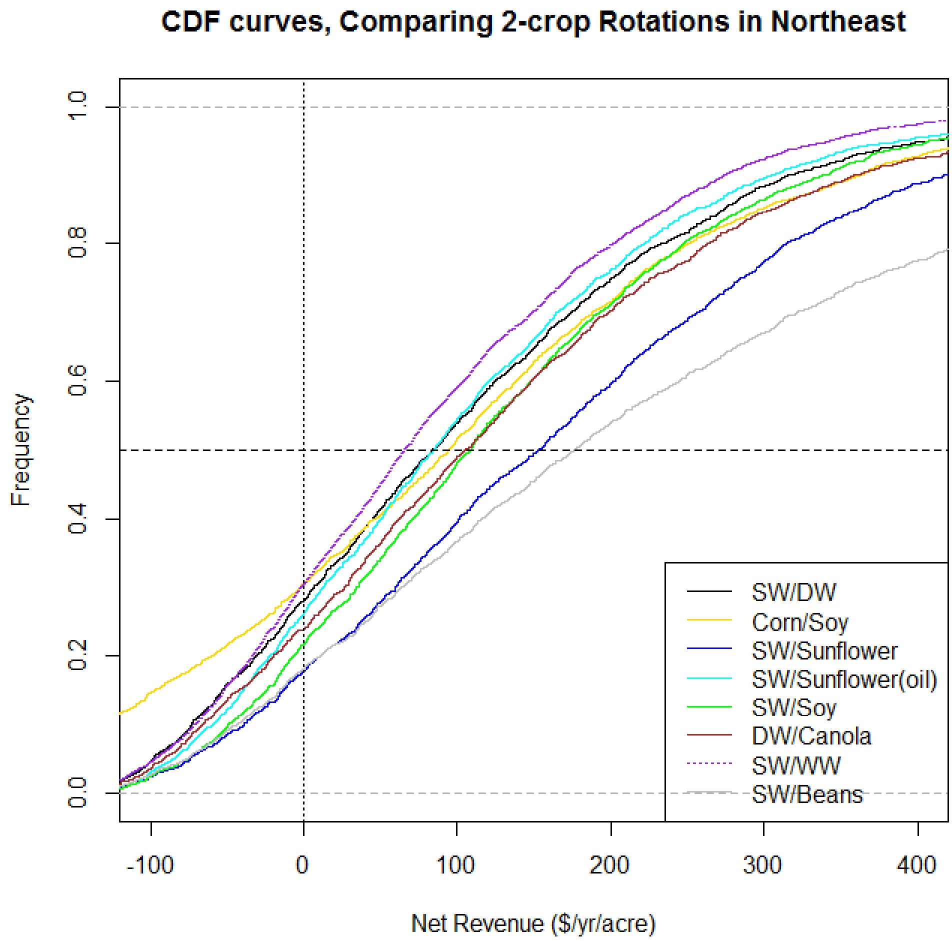

Figure C7: CDF curves for two-crop rotations, Northeast region.

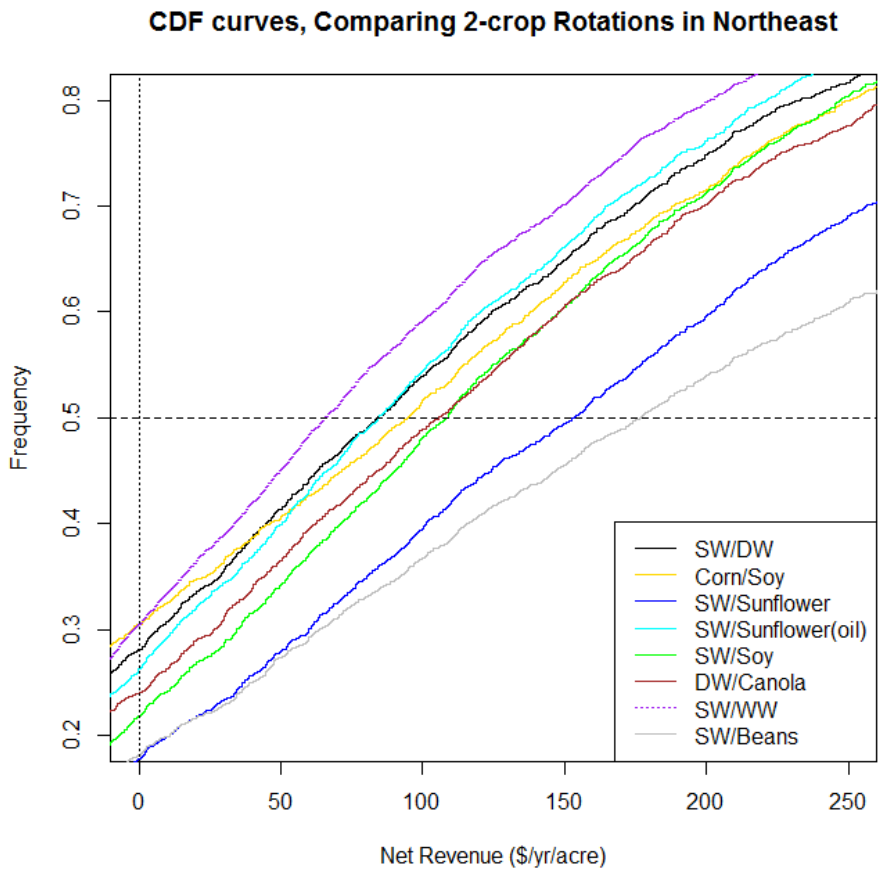

Figure C8: CDF curves for two-crop rotations, Northeast region, enlarged for detail.

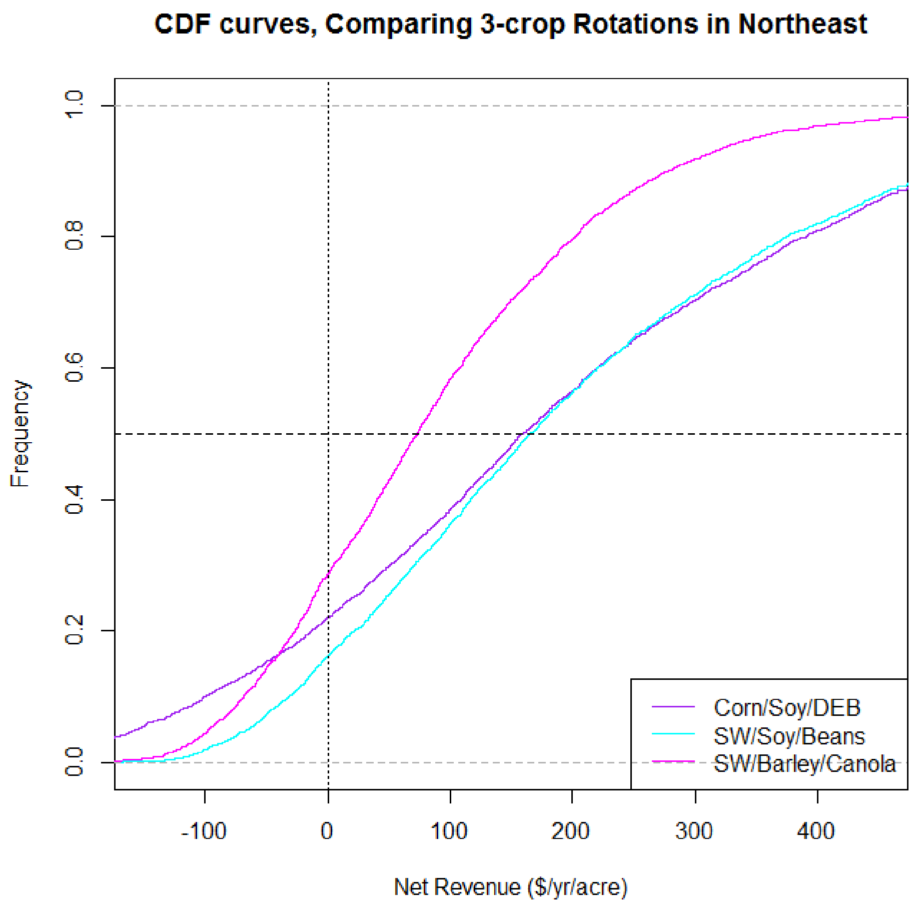

Figure C9: CDF curves for three-crop rotations, Northeast region.

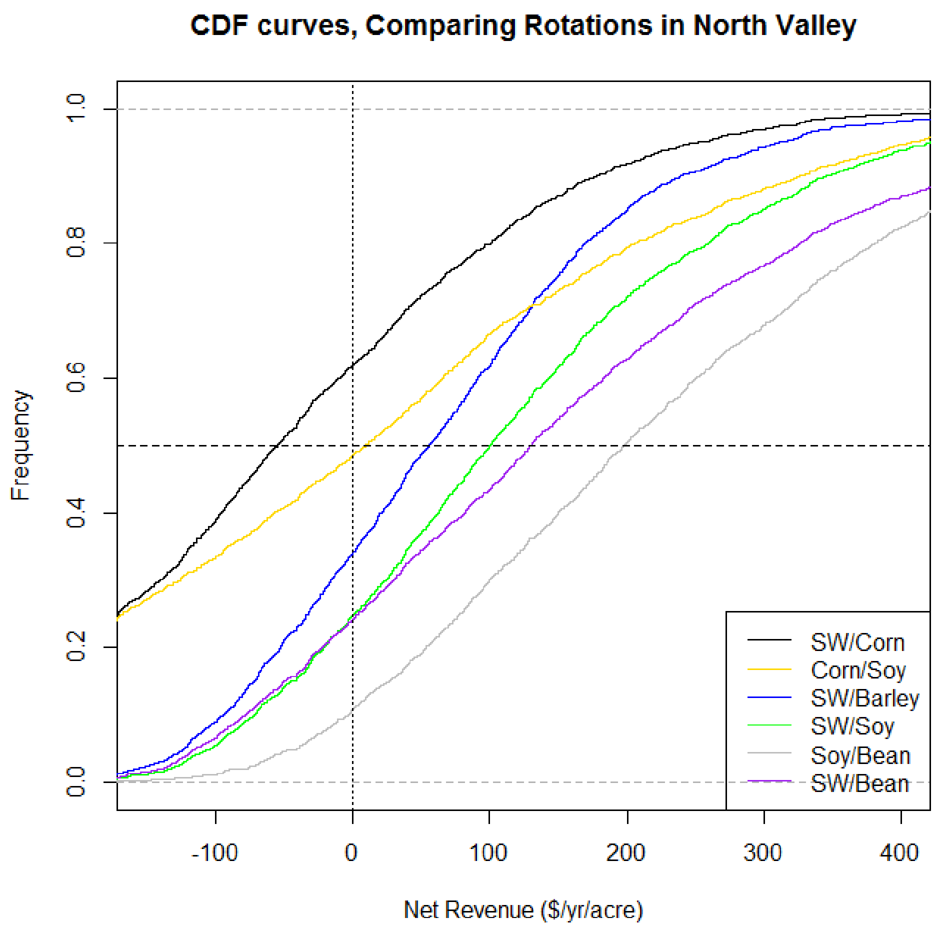

Figure C10: CDF curves for crop rotations, North Valley region.

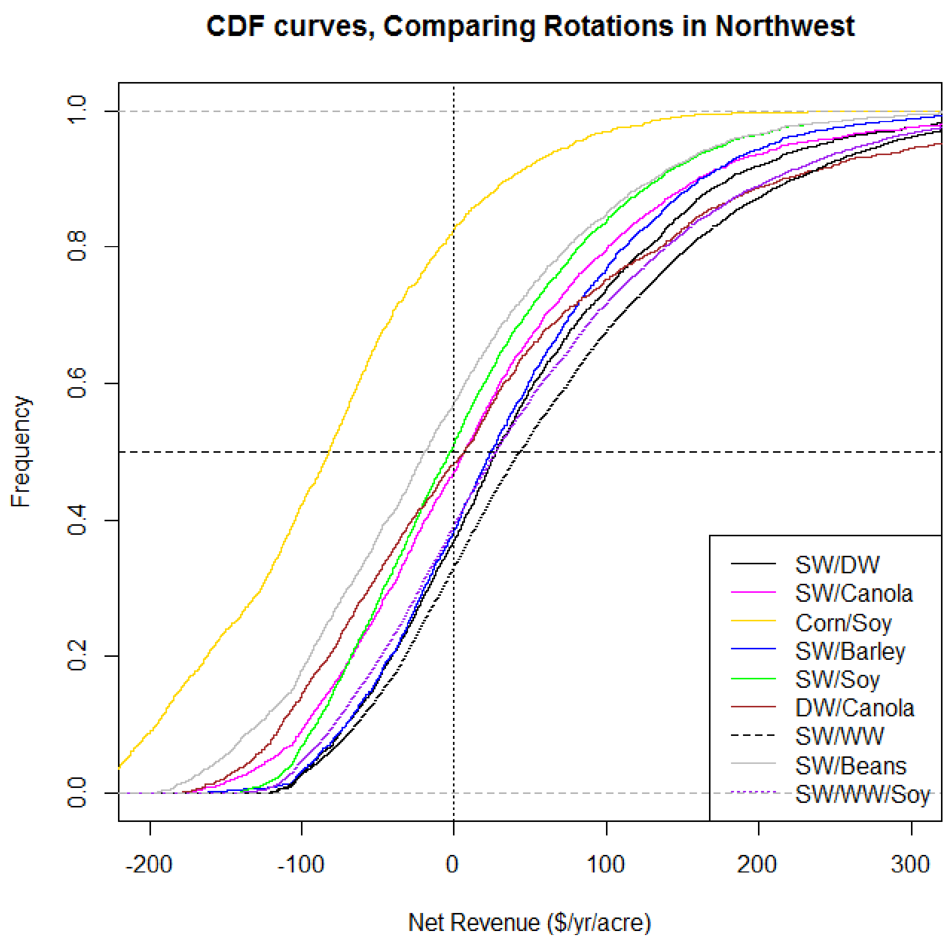

Figure C11: CDF curves for crop rotations, Northwest region.

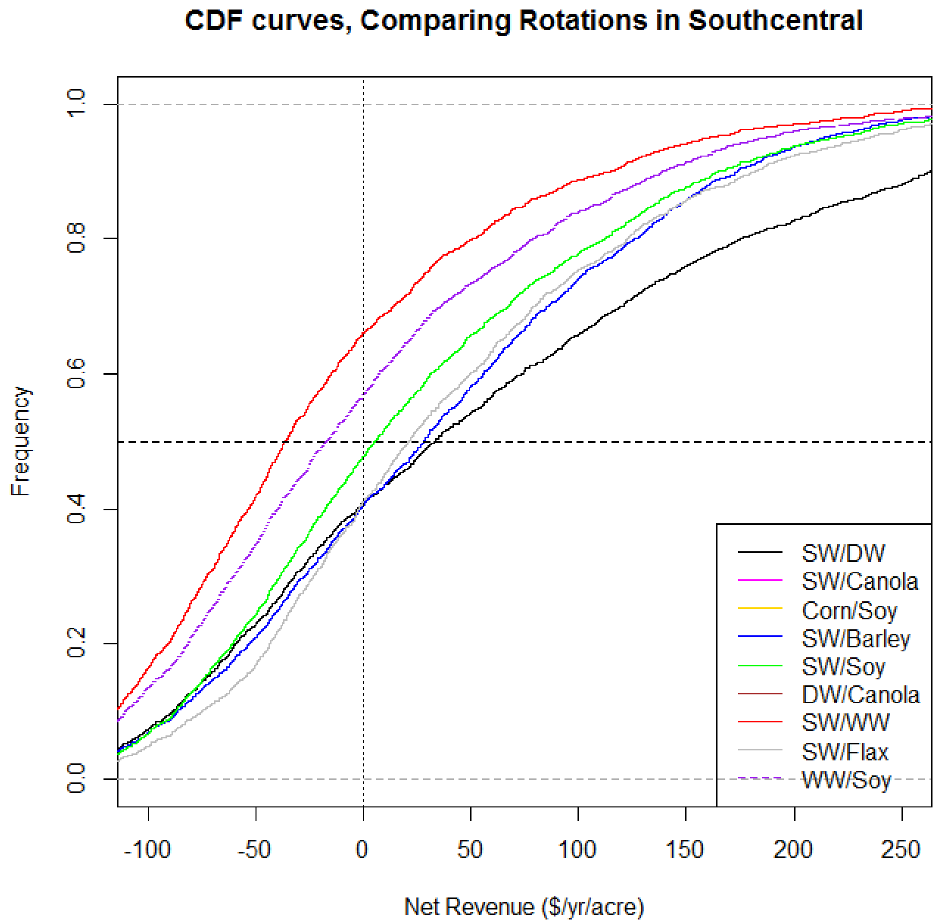

Figure C12: CDF curves for crop rotations, South Central region.

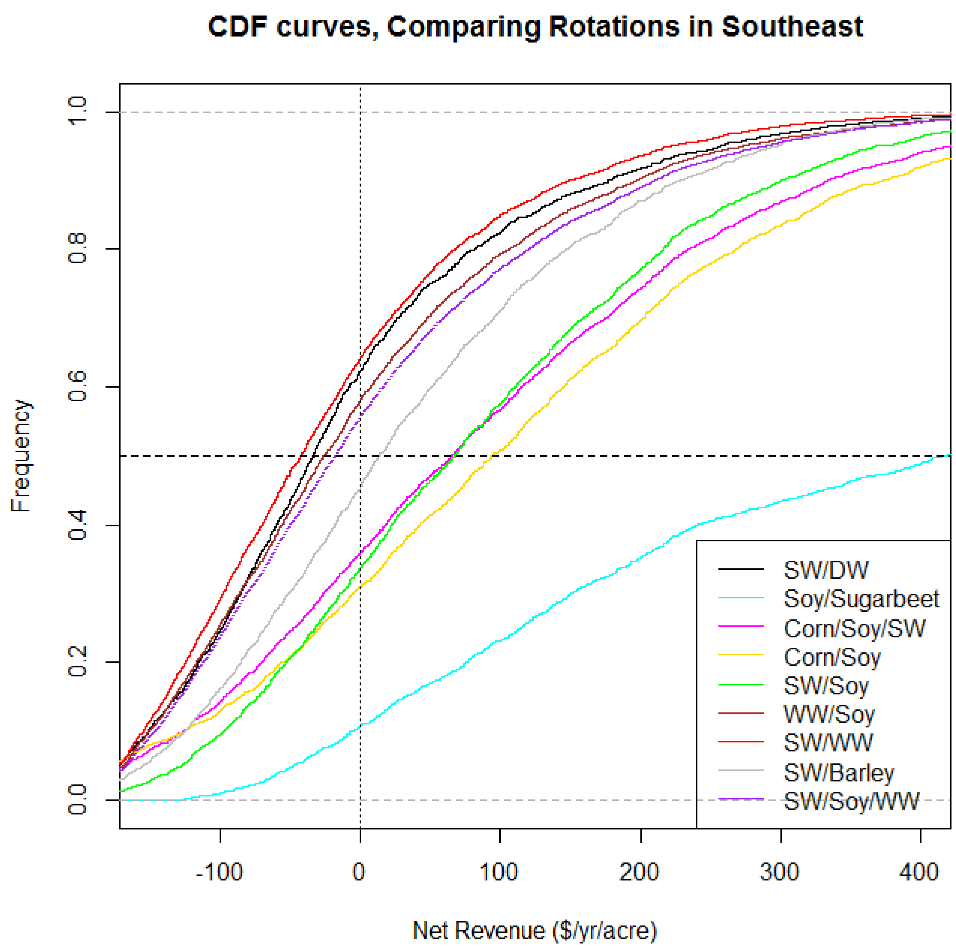

Figure C13: CDF curves for crop rotations, Southeast region.

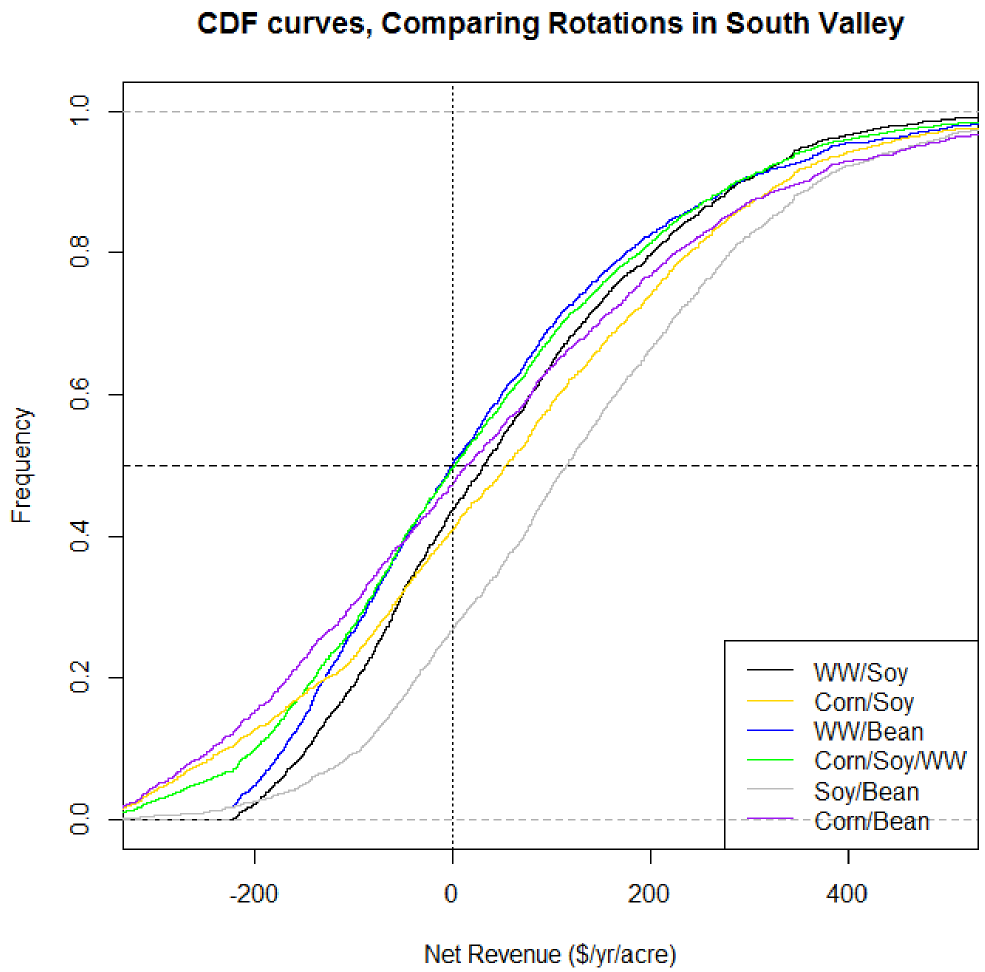

Figure C14: CDF curves for crop rotations, South Valley region.

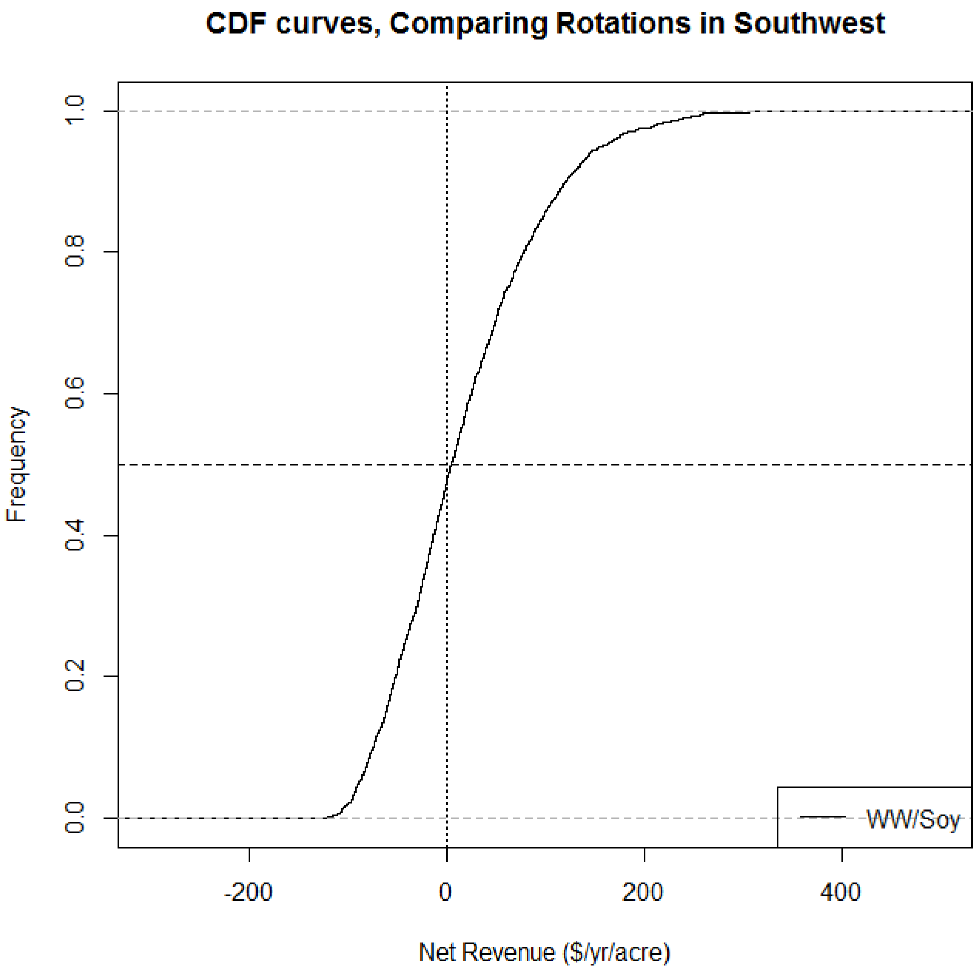

Figure C15: CDF curves for crop rotations, Southwest region.